Explaining Bank Stock Performance with Crisis Sentiment*

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ABSTRACT

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Keywords: Financial crisis, bank performance, investor sentiment.
JEL Classification: G21, G01, G02.

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1 Introduction

During the recent financial crisis, shareholders of banks suffered extreme losses on their investments. Not surprisingly, several recent studies in the financial economics literature (see, e.g., Fahlenbrach and Stulz, 2011; Beltratti and Stulz, 2012; Fahlenbrach et al., 2012; Berger and Bouwman, 2013) have tried to explain the bad stock performance of banks during the crisis focusing on differences in the banks' business models, capital structures, corporate governance, and regulatory environments. In this paper, we identify crisis sentiment as a previously neglected significant determinant of banks' stock performance. We show that losses of bank stocks were significantly driven by noise trading due to irrational market-wide (and to a lesser degree by firm-individual) crisis sentiment.

The question why some banks performed poorly during the crisis while others did not is addressed by an increasing number of studies in the literature. For instance, Aebi et al. (2012) and Fahlenbrach and Stulz (2011) investigate the question whether better risk management-related corporate governance mechanisms and management incentives influenced bank performance during the crisis. In contrast, Fahlenbrach et al. (2012) show that U.S. banks predominantly stuck to their risk culture between crises, with banks that performed poorly during the LTCM crisis also having a worse stock performance during the recent financial crisis. Next, Beltratti and Stulz (2012) find that banks with less leverage and lower returns immediately before the crisis performed better during the crisis. Furthermore, differences in bank regulations across countries appear to have played no significant role for banks' stock performance. Finally, Berger and Bouwman (2013) conclude in their study that higher bank capital improves the performance of banks while Wisniewski and Lambe (2013) find evidence that pessimistic press coverage Granger-caused the returns on banking indices during the Subprime Crisis.

There now exists ample empirical evidence that investor sentiment is significantly correlated with firms' stock returns. For example, several studies find evidence that investors can only pay limited attention to an asset and that this heterogeneous attention influences asset prices.[1] Fur-

[1] See, e.g., Barber and Odean (2008); Hirshleifer and Teoh (2003); Seasholes and Wu (2007).

thermore, De Long et al. (1990) show that asset prices are affected by uninformed noise traders who base their investment decisions on sentiment instead of rational information. Noise traders' decisions are unpredictable causing asset prices to become more volatile. Additionally, investors are usually risk averse which in turn limits their willingness to take positions against noise traders. Thus, prices can diverge significantly from fundamental values even in the absence of fundamental risk.

In contrast, the question whether investor and crisis sentiment affect the stock performance of financial and non-financial firms in the same way, has not been answered. There are, however, several reasons why one should suspect a differential effect of crisis sentiment on the stock performance of banks and non-financial companies. On the one hand, negative sentiment towards the state of the financial system should lead uninformed investors to devalue stocks of banks disproportionately more than the equity of non-financial firms. On the other hand, in a flight to presumed safety, uninformed traders could favor stocks of banks over stocks of non-financial firms during a crisis as banks are more likely to receive a government bailout.[2]

Several measures of investor sentiment have been proposed in the literature. For example, Shu (2010) examines the relation between investor mood and asset prices using mood proxies such as biorhythms and weather. Baker and Wurgler (2006) show that investor sentiment may have a significant impact on the cross-section of stock prices. They use six proxies for sentiment to form a composite sentiment index based on the proxies' first principal component. In a related empirical study, Tetlock (2007) shows that high media pessimism causes stock prices to move downward followed by a reversion to fundamental values.

In this study, we employ three different direct measures of crisis sentiment. We concentrate on relatively new measures that are based on Google search volume data. The usefulness of search volume data in finance has only recently been emphasized in the literature and is used increasingly to proxy for the interest in various economic and non-economic variables. Examining the U.S. unemployment rate, Ettredge et al. (2005) were among the first to suggest that search volume

[2] Gandhi and Lustig (2015) find strong empirical evidence that supports this idea as they document a size discount in the returns on bank stocks.

data is valuable for forecasting economic statistics. In the field of epidemiology, Ginsberg et al. (2009) and Polgreen et al. (2008) examine health trends and predict influenza epidemics. They use the Google and Yahoo! search engines to directly count internet queries. In economics, Choi and Varian (2009) describe how search data from Google could be used to predict several key economic figures such as automobile demand and vacation destinations. Da et al. (2010) employ the Google Search Volume Index (GSVI) of a firm's products to predict the earnings surprises of that firm. Kristoufek (2013) and Preis et al. (2013) examine whether Google search volume data may be used for portfolio diversification and investment strategies. Finally, Da et al. (2011) propose to use search volume data to measure investor attention. In their asset pricing study, they find evidence that the Google Search Volume Index measures the attention of retail investors quite well.

Internet search data make it possible to directly and objectively reveal the sentiments of a large number of households. Obviously, Google is most adequate to use search data since it is the largest search engine in the world. According to Hitwise (2009), by March 2009, it accounted for 72.39% of all U.S. searches.

As a first measure of crisis sentiment, we compute the General Crisis Sentiment Index (General CSI) developed by Weiß et al. (2013) which measures the extent of market-wide crisis sentiment. This index is the first principle component of the four crisis-related search terms "financial crisis", "credit crisis", "bank crisis", and "subprime crisis". The second index we use is the Crisis Sentiment Index (CSI) of Weiß et al. (2013) which measures the investors' perception of the relation between the financial crisis and individual banks' stocks. This index combines the search volume of the crisis-related search terms of the General Crisis Sentiment Index with the search volume of the individual banks' ticker symbols. As a third measure, we employ the Financial and Economic Attitudes Revealed by Search (FEARS) index developed by Da et al. (2015) which has been proven to predict aggregate market returns. It is computed using thirty economic search terms and hence, it is an additional measure of market-wide crisis sentiment.

We compute these measures of crisis sentiment on a quarterly basis for an international sample of 413 banks and 756 non-financial firms in the period from January 2004 to December 2012. As a proxy for the stock performance of these firms, we calculate the quarterly buy-and-hold returns of banks and non-financials during this time period, yielding a panel data set of 14,868 firm-quarter observations for banks and 27,216 firm-quarters for non-financial firms. In the second step of our analysis, we perform both univariate and multivariate analyses on the relation between the crisis sentiment indices and individual firms' stock performance, controlling for various alternative determinants of firms' stock returns. Most importantly, we control for the exposure of banks to systemic risk by including the Marginal Expected Shortfall (MES) developed by Acharya et al. (2010) in our analysis.

The results show that the performance of banks during the period from January 2004 to December 2012 is indeed driven by investors' irrational market-wide crisis sentiment, regardless of the banks' size. Furthermore, we find that idiosyncratic crisis sentiment does not have a significant impact on bank performance during that period. During the financial crisis, however, not only market-wide crisis sentiment predicts the banks' stock returns, but also idiosyncratic crisis sentiment is found to influence the buy-and-hold returns of large banks. This effect is both statistically and economically significant. These findings hold in a battery of robustness tests. For our sample of non-financial firms, we find virtually the same results as for banks but with one important difference: In contrast to banks, market-wide crisis sentiment has a significantly stronger impact on the stock returns of non-financial firms than on those of banks. We find evidence that supports the notion of noise traders considering investments in bank stocks safer than investments in non-financial companies as the effect of crisis sentiment on bank stock returns is strongest for banks of low systemic relevance.

The rest of this paper is structured as follows. Section 2 describes the data and variables used in the empirical study and presents descriptive statistics. Results are presented and discussed in Section 3. Section 4 concludes.

2 Data and variables

This section describes the data used in our empirical study as well as the measures of crisis sentiment and various control variables.

2.1 Sample construction and data sources

In our analyses, we construct a large sample of international banks. We focus on international banks for two reasons: First, crisis sentiment might vary significantly across countries because of differences in internet availability and usage across countries. Consequently, we expect a higher effect of crisis sentiment on the stock performance of banks in countries with a higher internet availability. Second, since the financial crisis originated from the U.S., crisis sentiment might have a different effect on banks' stock performance in the U.S. than in non-U.S. countries.

We start the construction of our sample by taking all banks from the active and dead-firm lists of *Thomson Reuters Financial Datastream*. To be included in our sample, we require all banks to be listed on a stock exchange with share price data being available from *Datastream*. Financial accounting data are retrieved from *Thomson Worldscope*. As currency risk might lead to biased results, we collect all data in U.S. dollars. We follow Fahlenbrach and Stulz (2011) and first consider all banks with Standard Industry Classification (SIC) codes between 6000 and 6300. We exclude banks with SIC code 6211 (Security Brokers or Dealers) because pure brokerage houses are included in this code, and banks with SIC code 6282 (Investment Advice) because these firms are not in the lending business. Next, we delete all OTC traded stocks, American Depositary Receipts (ADR), and secondary listings as well as preference shares. It is important that the banks in our sample are large enough in terms of total assets so that retail investors give them sufficient attention on the internet. We therefore exclude all banks which had less than $ 10 billion of total assets at the end of the fiscal year 2004. Our sample period ranges from January 2004 to December 2012. We lose several banks due to missing stock price or accounting data for that period. Our final sample consists of 413 banks and 14,868 bank-quarter observations, respectively. A list of all banks included in our study is given in Appendix A.1. In addition to our sample of banks, we also build an international sample of non-financial firms to analyze the differential effect of crisis sentiment on the stock performance of banks and non-financial firms.[3]

2.2 Measures of crisis sentiment

As our main explanatory variables to proxy for investor sentiment, we use three different market- and firm-level indices. To capture market-wide crisis sentiment, we employ the General CSI of Weiß et al. (2013) and the FEARS index of Da et al. (2015). To capture individual crisis sentiment, we use the CSI proposed by Weiß et al. (2013). All three indices are computed using the Google Trends analytics tool. Google Trends allows the user to download the Google Search Volume Index (GSVI) for given search terms. For all search terms or lists of terms which are entered in Google Trends, the tool returns data on the daily or weekly search volume for a chosen period scaled by the period's maximum. An example of the graphical output of weekly Google search volumes from Google Trends is shown in Figure 1.

— insert Figure 1 here —

We download all data from *Google Trends* based on global search queries. In addition to our proxies for investor sentiment, we also employ several control variables that might affect a bank's performance in our panel regressions. An overview of all variables and the respective data sources is given in Appendix A.2. In the following, we discuss all variables in detail and comment on selected descriptive statistics of our variables.

2.2.1 General Crisis Sentiment Index

De Long et al. (1990) argue that noise trading by individuals can lead to large price movements and thus, to differences in the underlying fundamental values of an asset. Indeed, the theoretical

[3] We build the international sample of non-financial companies by taking the constituent companies included in the S&P Global 1200 stock index as our basis. As a first step, we exclude every financial firm in the sample using the firms' Standard Industry Classification (SIC) code (6012-6799). Next, the company list and the data are filtered in a similar way as it was previously done for our sample of banks. Additional data filters for our sample of non-financial companies are described in Section 2.2.2

literature suggests that bad financial information and noisy signals can cause tremendous negative effects that could result in bank runs or investors exiting investments (see Gorton, 1988; Morris and Shin, 2001; Goldstein and Pauzner, 2005; Mendel and Shleifer, 2012). It is argued that even incremental changes in the information environment of investors can lead to significant changes in their behavior. For example, Doblas-Madrid (2012) provides a theoretical framework in which the derived probability of investors selling before crashes increases with the amount of noise present in the economy. Recently, the events during the financial crisis with the collapse of Lehman Brothers as its climax generated an unprecedented attention of the media and the public towards the financial market. Consequently, the negative sentiment present at that time might have been an additional driving factor of the stock returns of financial institutions. To empirically assess this hypothesis, we introduce a market-wide measure of investors' sentiment towards turmoil in the financial market during a crisis.

In order to measure the pessimistic market-wide sentiment of retail investors during the financial crisis, we compute a General Crisis Sentiment Index as a direct measure of crisis sentiment. To compute the index, we obtain the GSVIs for several variations of the search term "financial crisis". In particular, we download weekly data for the terms "financial crisis", "credit crisis", "bank crisis", and "subprime crisis" from January 1, 2004 to December 31, 2012. We restrict ourselves to these four search terms and do not employ words in our study that differ only marginally from them, e.g., "banking crisis", because the alternative words are highly correlated with the words we use.[4] Also, we only use English words to proxy for the level of worldwide crisis sentiment. Generally, it is very likely that the inhabitants of non-English speaking countries use their mother tongue when searching on the internet. We therefore translate the four crisis-related phrases into every language spoken by the majority of the population of all countries in our sample. For each country, we restrict the *Google Trends* output to the respective geographical area and compare the translated search terms to their English versions. In some cases the average search volume of the

[4] For example, the time evolution of the GSVIs of "subprime crisis" and "mortgage crisis" show a correlation of more than 95%. To check for synonyms and additional search terms, we type in the four crisis-related search phrases to get "related search terms" from *Google Trends*. However, this procedure yields no relevant or new search terms that need to be added to our set of phrases.

local language exceeds the volume of the English crisis words. [5] Comparing all combinations of the four crisis-related English search terms above and its respective translation shows that the time evolutions of the GSVIs are in fact in each case highly correlated. Since we have no information on the actual level of Google searches on the phrases but rather on the relative time evolution, we are able to restrict our analysis to the use of the four English phrases.

To calculate the index, we follow Baker and Wurgler (2006) and conduct a principal component analysis with the GSVIs for the four search terms. The results for the first principle component are then used as a proxy for the Google search volume of crisis-related search terms and are thus our primary proxy for the general crisis sentiment of investors. To avoid a possible look-ahead bias in the resulting time series of the principal component analysis, we calculate the index with an extending estimation window. First, we estimate the first principal component for the year 2004 by using the first 52 GSVI values of each of the four time series. For the remaining time period, we conduct the analysis for each week separately by extending the considered time interval by one week after each estimation. To be precise, we compute the first principle component in week t on data for week one through week t. After computing the first principal component for each week, we scale the resulting time series as it is done in the *Google Trends* tool. We divide by the maximum value of the time series and then multiply the values by 100. We then define Z_t as the resulting value of the first principle component at time t. A comparison between the time evolution of the crisis sentiment Z_t and the GSVIs of the four crisis-related search terms is shown in Figure 2.

— insert Figure 2 here —

As expected, crisis sentiment increased in the middle of 2007, experiencing a peak around the collapse of Lehman Brothers in 2008. From the end of 2008 onwards, crisis sentiment slowly decreased but at the end of 2012 it was still higher than before the crisis. It should be noted that

[5] For example, comparing the search volume of “financial crisis” with the Swedish translation “finanskris” (and restricting the area to Sweden) reveals that the Swedish version has, on average, a higher search volume in Sweden. However, we also observe that the time evolutions of the GSVI for “financial crisis” and “finanskris” are very similar and that the time series indeed have a correlation of approximately 93%. This circumstance is by far not restricted to the example used here.

during the time of the crisis, the search term “subprime crisis” was the main driver for the increase in the curve of crisis sentiment. But this is not unexpected as the data is normalized and the term “subprime crisis” especially applies to the recent financial crisis, whereas the other search terms may also apply to previous financial crises.

2.2.2 Crisis Sentiment Index

The second crisis index we employ in our empirical study is the CSI of Weiß et al. (2013) as a measure of the investors’ perception of the relation between the financial crisis and individual banks’ stocks. In their study, they find evidence that the CSI influenced stock returns of larger insurance companies negatively during the financial crisis. We employ this measure of crisis sentiment to examine whether banks were also affected by idiosyncratic crisis sentiment. Following Da et al. (2011), we download the weekly GSVI for each bank for the time period between 2004 and 2012. An investor searching in Google for information on bank stocks may either use the company name or its ticker symbol. If possible, we obtain the data for the ticker symbol for several reasons. First, people may search the company name for reasons unrelated to investing. In the context of banks, e.g., customers may search for the bank name to compare the products and prices to those of other banks. Secondly, investors may use variations of the company names. BNP Paribas, e.g., may be searched with “BNP Paribas”, “BNP” or “Paribas”. Ticker symbols, in contrast, are uniquely assigned and it is likely that internet users searching for ticker symbols are investors interested in information on the banks’ stocks. If the ticker symbol is numeric (e.g., for Japanese banks), however, we use the name of the bank, which we retrieve from the *Worldscope* database, to download the GSVIs. If there are several possibilities to search for the bank name, we test all possibilities and examine the GSVIs’ time evolution to see if there are visible differences. In all these cases, differences between the respective GSVIs have been insignificant. In a few cases, a bank’s ticker symbol also had a generic meaning or was a common abbreviation in the English language, like, e.g., “CRAP”, “BP”, “ETE”, “C”, or “MTB”. These search terms either had unusually high GSVIs or showed distinctive seasonal fluctuations. We then used the name instead of the ticker symbol of the bank as a search term in *Google Trends*.[6]

To calculate the CSI, we first estimate the correlations ρ_t^i between the $GSVI_t^i$, which is the GSVI for bank i, and the general crisis sentiment Z_t at time t. To ensure that the correlations do not suffer from a look-ahead bias, we use rolling windows to estimate ρ_t^i. The first 52 values are estimated with a window extending on data for week one to week t. For the remaining period, we estimate the correlation at time t using rolling windows with a length of 52 weeks with right interval boundary at t, so in each estimation the windows are shifted forward one week. The CSI for bank i at time t is then defined as

$$CSI_t^i := \left(\frac{GSVI_t^i + Z_t}{200}\right) \cdot \rho_t^i.$$

In Figure 3, we plot the time evolution of the mean CSI values as well as the empirical 10%- and 90%-quantiles, which are computed separately for each point of time, and across our full sample of banks and non-financial companies over the whole sample period.

— insert Figure 3 here —

Similar to the time evolution of the General Crisis Sentiment Index, we notice a slight increase in crisis sentiment at the beginning of the financial crisis in the middle of 2007. Until the middle of 2008, the graph of the mean CSI values declines to almost zero. In the middle of 2008, however, CSI increases drastically, probably in response to the collapse of Lehman Brothers. Analyzing the evolution of the CSI of a global sample of non-financial companies reveals a similar pattern. However, the mean value of non-financial firms' CSI remains relatively flat over time, while we observe drastic changes during the crisis for the mean and the 90%-quantile values of banks' CSI which are much higher. To illustrate the (univariate) relation between the CSI and the banks' stock prices, Figure 4 shows a comparison between the estimated values of the CSI of Citigroup, JP Morgan Chase, BNP Paribas, and HSBC and their respective stock prices during the sample

[6] For our sample of non-financial companies, we filter our sample in a similar way by manually screening the list of ticker symbols and detect combinations with ambiguous meaning. In total, we end up with a sample of 756 non-financial firms.

period.

— insert Figure 4 here —

It is apparent that during the crisis, the level of crisis sentiment is particularly high for all of the four banks. Comparing the two U.S. banks Citigroup and JP Morgan Chase, we can observe a similar time evolution of the CSI. Both graphs are about zero until the end of 2008, after which both indices increase significantly. Afterwards, both graphs gradually decrease until they are again close to zero. The evolution of their stock prices, however, is different. During 2008, the stock prices of both U.S. banks decrease. In 2009, the stock price of JP Morgan Chase recovers to a certain extent, whereas the stock price of Citigroup remains low. The time evolutions of the CSI of the European banks BNP Paribas and HSBC differ from the evolution of the CSI of the two U.S. banks as well as from each other. We observe considerably lower peaks for the European banks than for the U.S. banks in 2008. This is consistent with the fact that the crisis emerged in the U.S. and hence, banks in the U.S. received considerably more media attention during the crisis (especially after the collapse of Lehman Brothers). Both European banks already had high CSI values in 2007, but the time evolution of the CSI of BNP Paribas is more volatile than the evolution of the CSI of HSBC. We also notice differences in the time evolution of the stock prices of European banks. The stock prices of BNP Paribas suffered heavily during the financial crisis, whereas shareholders of HSBC stocks lost only little in their stock investments. Comparing the four banks' CSI with their respective stock prices, we notice that both individual crisis sentiment and the banks' stock returns appear to significantly co-move. Later in our panel regression, we test whether lagged values of both market-wide and individual crisis sentiment can also be used to predict a bank's stock performance.

2.2.3 FEARS index

To complement the two proxies for crisis sentiment, we also employ the so-called FEARS index as proposed by Da et al. (2015) in our analysis. The idea behind this index is to capture the aggregate sentiment of households towards the economy, using search terms that are related to the overall state of the economy. Da et al. (2015) show that the FEARS index can predict reversals in short-term returns as well as short-term market volatility. We employ the index in our analysis to examine whether it can be used to predict banks' stock returns as well. To compute the index, Da et al. (2015) examine 118 search terms with either a positive or negative connotation and find that negative terms have the largest influence on returns. We follow their evaluation and compute the FEARS index using the thirty most influencing search terms from their analysis. The search terms used in our analysis are listed in Appendix A.3.

Differing from Da et al. (2015) who use daily data, we download the weekly GSVIs for the time period between 2004 and 2012. Then, we compute the weekly changes in search term j in the following way:

$$\Delta GSVI_t^j = \ln\left(GSVI_t^j\right) - \ln\left(GSVI_{t-1}^j\right).$$

We observe the same issues with seasonality and heteroscedasticity for the weekly data as Da et al. (2015) find for daily data and thus proceed in the same way. First, we winsorize each original GSVI time series at the 5% level to eliminate outliers. Next, we regress $\Delta GSVI_t^j$ on month dummies and keep the residual to eliminate seasonalities in the data. Then, we scale each time series by its standard deviation to minimize heteroscedasticity. Let $\Delta AGSVI_t^j$ be the adjusted, i.e., winsorized, deseasonalized and standardized weekly change in search term j. The FEARS index is then defined as

$$FEARS_t := \frac{1}{30}\sum_{j=1}^{30} \Delta AGSVI_t^j.$$

In Figure 5, we plot the quarterly time evolution of the FEARS index over our sample period from 2004 to 2012.

— insert Figure 5 here —

The plot of the FEARS index shows that the biggest change in search behavior occurred in the last quarter of 2008. However, the plot given in Figure 5 does not clearly show evidence in support of a significant correlation between the FEARS index and banks' stock returns.

2.3 Control variables

In our panel regressions, we include three groups of control variables which are described in the following.

The first group of control variables contains several idiosyncratic bank characteristics. Data on these variables are obtained from the *Thompson Worldscope* database. First of all, we include the logarithm of the banks' total assets and the logarithm of net revenues in our panel regressions to control for a bank's size. It could be argued that larger banks perform better during a crisis because shareholders depend on the bank being too-big-to-fail (or too-interconnected-to-fail). Gandhi and Lustig (2015) find empirical support for this view as they observe that bank stock returns exhibit a discount for firm size that reflects implicit bailout guarantees during financial crises. Aebi et al. (2012), however, find a negative influence of the banks' size on their stock returns during the financial crisis. We therefore have no expectations regarding the sign of the coefficients of Total assets and Net revenues in our regressions. To proxy for a bank's profitability, we employ the bank's Return on assets. Here, we naturally expect a positive influence of bank profitability on the stock performance of banks.

In this study, we examine the effect of crisis sentiment and noise trading on bank performance. It is possible that not sentiment was the driver of the plummeting stock prices during the crisis, but that investors made rational decisions and sold stocks of banks that were indeed significantly exposed to systemic risk. To control for this possibility, we employ an established measure of a bank's exposure to systemic risk. We compute the MES developed by Acharya et al. (2010), which is defined as the negative mean return on a bank's stock calculated on the days the market experienced its 5% worst outcomes during our sample period. As a proxy for the market return, we use the *Datastream Bank Index*.

We follow Fahlenbrach et al. (2012) and additionally include the variables Market-to-book ratio and Distance-to-default in our empirical study. The market-to-book ratio is a common measure for a firm's value. It is defined as the market value of common equity divided by the book value of common equity. Fahlenbrach et al. (2012) report a positive relation between the market-to-book ratio and buy-and-hold returns of banks during the financial crisis. We therefore expect a positive influence of the variable Market-to-book on the stock performance of banks in our analysis. Distance-to-default as a proxy for the financial soundness of a bank is computed as the logarithm of the z-score. The z-score is calculated as a bank's equity to assets ratio plus return on average assets, divided by the standard deviation of the return on assets over a five year rolling window. A higher capital ratio and profitability will increase the z-score, whereas a higher return volatility will decrease it. Thus, higher z-scores indicate lower individual default risk and will consequently be reflected by a better stock performance (see Fahlenbrach et al., 2012; Uhde and Heimeshoff, 2009).

Next, we employ a bank's non-interest income which is defined as the ratio of non-interest income to the sum of non-interest income and net interest income. Here, we expect a higher income variability and a higher ratio of a bank's non-interest income to interest income to be indicative of a riskier business model (see Brunnermeier et al., 2012; Fahlenbrach et al., 2012).

Additionally, we include the variable Loans defined as total loans divided by total assets in our regressions. Beltratti and Stulz (2012) argue that banks with higher loans possess a smaller portfolio of securities and also fewer assets marked to market. These banks are expected to perform better because, e.g., a possible increase in credit spreads (which reduces security values) would have a smaller impact on their regulatory capital. Finally, we include the variable Tier 1 capital in our analyses. Fahlenbrach and Stulz (2011) find a positive influence of the Tier 1 capital ratio on buy-and-hold returns during the financial crisis. Thus, we also expect a positive sign of Tier 1 capital in our regressions as a better capitalization of banks (and consequently a better financial soundness) should decrease a bank's default risk during times of market stress.

The second group of control variables that we use contains several proxies for macroeconomic conditions. Data on this group of variables are obtained from the *World Development Indicator* (WDI) database of the World Bank. As a control variable for overall economic conditions and business cycle fluctuations, we employ the annual growth rate of the real gross domestic product (GDP) in percent. The banks' investment opportunities may be correlated to business cycles. In times of economic growth, investment opportunities rise and thus, a positive effect of the GDP growth rate on bank performance may occur. Moreover, in times of economic growth, banks may pro-cyclically build up more capital in anticipation of an upcoming economic downturn (see Uhde and Heimeshoff, 2009).

Furthermore, we include the inflation rate defined as the logarithm of the annual change of the GDP deflator. Demirgüç-Kunt and Detragiache (1998) find evidence that both a low GDP growth and a high inflation rate increase the likelihood of systemic banking sector problems which could worsen the stock performance of banks through spillover effects.

As a measure of liquidity in the respective country's stock market, we employ the variable Stock Market Turnover defined as the ratio of annual trading volume to shares outstanding (see Vermeulen, 2013). As a fourth macroeconomic control variable, we employ the variable Internet use which is the number of internet users in a bank's home country per 100 people. Results of international studies that use internet search volume data might be distorted by differences in internet availability across countries and thus, we employ the variable Internet use to control for this potential bias.

Since we have an international sample of banks operating in different regulatory regimes, we additionally include regulatory control variables in some of our regressions. In their study on bank performance during the credit crisis, Beltratti and Stulz (2012) employ variables to control for the power of the regulators, oversight of bank capital, restrictions on bank activities, and the independence of the supervisory authority. We also employ these variables, which were developed by Barth et al. (2004), in our analysis.[7]

Anginer et al. (2014) find evidence that deposit insurance, possibly due to existing moral hazard, has a destabilizing effect on bank risk in good times and a stabilizing effect in times of crisis. Therefore, we additionally include the variable Deposit insurance constructed by Barth et al. (2004) in our study. It is a dummy variable which takes on the value of one if a country has an explicit deposit insurance scheme in place and if depositors were fully compensated the last time

[7] The authors provide the dataset on their website http://business.auburn.edu/ barthjr/Web%20Dataset.htm.

a bank failed, and zero otherwise.

2.4 Bank performance and descriptive statistics

Table I reports descriptive statistics on buy-and-hold returns, our measures of crisis sentiment, and the control variables which are employed in our analysis.

— insert Table I here —

The summary statistics are given for our full sample of 413 banks for the period from Q1 2004 to Q4 2012. First, we notice that the average buy-and-hold return is negative with -2.0% over our full sample period. To examine the stock performance of banks more closely, we compute average values for the banks' buy-and-hold returns before, during, and after the financial crisis.

Because several GSVIs for banks in our sample are missing, we compute the CSI for 337 banks. Over our full sample period the mean and median values of the CSI are approximately zero. The values increased significantly to a maximum value of 0.52 during the financial crisis. The General Crisis Sentiment Index has a mean value of 8.97 and is more than five times higher during the financial crisis with a maximum value of 48.4. Similar to the CSI, the FEARS index has a mean value of approximately zero and a maximum value of 0.47. The standard deviation of the FEARS index, however, is more than twice as high.

Several additional findings in Table I are noteworthy. First, we observe an average MES of 0.8%. Hence, during the full sample period, banks were generally not significantly exposed to systemic risk. During the financial crisis, however, banks had a higher MES average value. Several banks were even heavily affected by systemic risk exposure stemming from the banking sector in this period, e.g., Aareal Bank with an average MES of 3.9%, Commerzbank with an average MES of 3.3%, and Citigroup with an average MES of 2.4%. Secondly, the mean value of our variable Internet use is quite high with approximately 58.2%. With almost two quarters of households having access to the internet, we can assume that retail investors use the internet to collect information on a regular basis. A cross-country comparison shows, however, that some countries have a significantly limited access to the internet, e.g., India with an average value of the variable Internet use of 5.7%. In addition, the mean and median Tier 1 capital ratios are both in excess of 9%, which means that banks, on average, were well-capitalized (see also Fahlenbrach et al., 2012). We notice a negative minimum value of the Tier 1 capital ratio, hence capital requirements are not fulfilled by all banks and at all times during our sample period. Furthermore, banks had a positive mean and median profitability and leverage ratio. The average total assets amount to $ 161.6 billion.

We are interested in how the statistics differ during normal times and times of crisis. For this purpose, we split our sample period in the time before (Q2 2004 - Q2 2007), during (Q3 2007 - Q4 2008), and after (Q1 2009 - Q4 2012) the crisis and report important statistics in Table II (we follow Fahlenbrach et al. (2012) and Beltratti and Stulz (2012) and define the crisis period as Q3 2007 to Q4 2008).

— insert Table II here —

Before the crisis, the average buy-and-hold return was approximately 2.3%. During the financial crisis, banks recorded considerably higher average losses of -12.1%. As expected, the mean systemic risk exposure measured by a bank's MES is higher during the crisis compared to the period before. While we observe a higher maximum systemic risk exposure during the short crisis period than afterwards, the average values of MES are larger than during the crisis period. The same picture can be seen for individual default risk measured by the banks' distance-to-default since default risk after the crisis (Q1 2009 - Q4 2012) was higher than the average values from Q3 2007 to Q4 2008. However, when looking at the individual CSI of a bank, we find that mean, median, as well as the 5%- and 95%-quantile were considerably higher during the crisis and thus, could have played an important role in the pricing of bank stocks.

2.4.1 Univariate analysis of the variables

In this subsection, we address the question whether idiosyncratic crisis sentiment influences bank performance by splitting our sample into top and bottom quartiles of the CSI. Table III presents a comparison of the descriptive statistics for our dependent and independent variables in the top and bottom CSI quartiles for the sample of 337 banks for which the individual GSVIs are available.

— insert Table III here —

As expected, buy-and-hold returns differ significantly at the 1% level between the top and bottom CSI quartiles. Banks in the bottom quartile had an average return of approximately −3.7% over our complete sample period, whereas the average return of banks in the top quartile was −8.7%. By construction, the CSI is significantly higher in the top quartile. Additionally, the General Crisis Sentiment Index differs significantly between the bottom and top quartile. The FEARS index, however, does not seem to be related to idiosyncratic crisis sentiment. Table III shows several significant differences for the control variables as well. For instance, banks in the top quartile of CSI had on average a higher MES and hence, a higher exposure to systemic risk, a lower market-to-book ratio, and a higher debt maturity. Surprisingly, total assets do not significantly differ between banks in the top and bottom quartile of CSI, hence it seems that banks were subject to increased investor sentiment irrespective of their firm size.

Next, we focus in more detail on the interplay of a bank's stock performance and the size of a bank, its sensitivity for systemic risk, and crisis sentiment. Table IV presents mean buy-and-hold returns on a bank's stock, sorted by the quintiles of total assets and MES or crisis sentiment, respectively.

— insert Table IV here —

Our first observation from Panel A of Table IV is that the higher a bank's exposure to systemic risk (higher MES), the worse its average stock performance (obviously, this result is in part due to the construction of the MES). However, we can not find any significant trend in the quintiles of MES regarding the size of a bank. Larger banks in the lowest quintiles of MES performed almost as well as their smaller counterpart (or equally bad in the higher quintiles). Turning to Panel B, we see a rather different picture. Sorted by CSI instead of MES, we observe negative mean buy-and-hold returns for almost all combinations of quintiles in total assets and the crisis sentiment index. Bank-quarters in the largest quintile of CSI are most affected by idiosyncratic crisis sentiment and obviously, on average, experienced even larger losses in stock value than bank stocks that are less sensitive to attention towards crises. This trend can be observed throughout almost all quintiles of total assets. Interestingly, mean stock performance seems to worsen with increasing size, no matter which quintile of CSI is used.

3 Empirical results

The results of the univariate analysis indicate that both idiosyncratic as well as market-level crisis sentiment had an impact on bank performance during the financial crisis. In this section, we investigate the relation between bank performance and crisis sentiment using panel regressions.

We conduct several sets of panel data regressions with buy-and-hold returns as the dependent variable using bank- and time-fixed effects. In each set, we employ either CSI, the General CSI, or the FEARS index to determine the impact of idiosyncratic or market-wide crisis sentiment on the stock performance of banks. To mitigate possible biases due to heteroskedasticity and serial correlation, we estimate all regressions with clustered standard errors to correct for heteroskedasticity. Moreover, there is the possibility that bank performance also affects the level of crisis sentiment, with plummeting bank returns simultaneously increasing the attention and sentiment of retail investors. To address this concern, all regressors are lagged by one quarter. Also, we winsorize the buy-and-hold returns and bank characteristics at the 2.5% and 97.5% level to minimize the risk of outliers driving our results.

In the following subsection, we discuss the results of these regressions of buy-and-hold returns on CSI, General CSI, and FEARS, respectively.

3.1 Baseline regressions

The results of our baseline regressions are shown in Table V.

— insert Table V here —

First, in columns (1) - (3) in Table V, we report results on panel regressions that involve our full sample of banks and either the idiosyncratic Crisis Sentiment Index, the General Crisis Sentiment Index, or the FEARS index proposed by Da et al. (2015), respectively.

In our first set of regressions, we include our proxies for idiosyncratic and market-wide sentiment and find a slightly significant influence of the General CSI on stock performance for our complete sample of banks. The individual CSI, which is not available for the full sample, does not seem to be a significant driver of average stock performance in the banking sector. Thus, we can confirm that higher levels of market-wide crisis sentiment predict lower buy-and-hold returns in the next quarter, while idiosyncratic crisis sentiment might not determine individual stock performance for every bank. In addition, the result obtained for the FEARS index in column (3) supports the hypothesis that market-wide crisis sentiment has a negative impact on banks' stock returns. However, the results from the regressions including the FEARS index have to be interpreted with caution. The search terms used to compute the index are not specifically related to financial crises but rather to economic downturns and crises in general. Raunig and Schleicher (2009) as well as Raunig (2011) find that investors distinguish between banks and other types of firms. Therefore, the FEARS index should be seen as a good proxy for investor sentiment in general rather than a measure of sentiment of investors who hold shares of banks. Consequently, the FEARS index should be a strong predictor for aggregate market returns but only a weak predictor for bank returns. The empirical results, however, indicate that the FEARS index is, nevertheless, a significant determinant of banks' stock performance.

Turning to the results for the control variables, we find evidence that bank size influences buy-and-hold returns negatively. This finding is in line with the results of Gandhi and Lustig (2015) who show that the stock returns of large banks are significantly lower due to the pricing of implicit bailout guarantees.

A higher market-to-book ratio increases stock returns, which is consistent with Aebi et al. (2012) who provide evidence that during the crisis there was a positive relation between the market-to-book ratio and banks' buy-and-hold returns. In contrast, a higher leverage ratio leads to worse stock performance of banks which supports the findings of Fahlenbrach et al. (2012) for the crisis period. Moreover, our variable Non-interest income enters the regressions with a significant positive sign while a bank's Default risk, Tier-1-capital, and Return on assets seem to play no relevant role in determining overall bank stock performance. Surprisingly, the exposure to systemic risk measured by the MES does not seem to have an influence on the performance of bank stocks.

For our next analysis, we restrict our full sample of banks to the fourth quartile of a bank's total assets and repeat the same regression analyses as in columns (1) - (3). From column (4) - (6) in Table V, we see that the effect of General CSI on stock performance is even stronger for larger banks (based on a comparison of the economic significance of market-wide crisis sentiment). A one standard deviation increase in General CSI leads to a decrease in stock performance of -0.6% (-0.0007×9.359) in our full sample regressions, which is less than the -2.1% (-0.0022×9.359) decrease in quarterly stock returns for larger banks.

It can be argued that our results may be biased because crisis sentiment was non-existent or very low from the beginning of 2004 until the onset of the financial crisis in 2006. Thus, in a further analysis, we restrict the sample to large banks and only cover the time period from 2006 to 2010. In these regressions, the General Crisis Sentiment Index remains statistically and economically significant at a similar level as in the regression in (5). This time, the FEARS index is omitted due to multicollinearity. Further, we find that, during the crisis years from 2006 to 2010, banks with higher loans to total assets ratios had lower stock returns.

3.2 Which banks are influenced by crisis sentiment?

In some of our baseline regressions, we restricted our sample of banks to a group of large banks to see how their stock performance is related to crisis sentiment. Extending the idea that crisis sentiment had a differential effect on certain sub-samples of banks, we try to answer the question whether sub-samples of banks that differed with respect to other variables also responded differently to the influence of individual and market-wide sentiment. Consequently, we split our sample according to the 25%- and 75%-quartile of the variables market-to-book ratio, leverage, MES, and default risk (distance-to-default) and perform panel regressions using the banks in the respective first and fourth quartiles.

The results from these analyses are shown in Table VI.

— insert Table VI here —

We can see that an increase in General CSI had a negative effect on banks in the first quartile of distance-to-default and thus, affects banks that have a higher probability of default. Financially healthier banks do not seem to be affected by market-wide crisis sentiment. Interestingly, we find a slight statistical significance of individual crisis sentiment over the whole time period for banks in the fourth quartile of distance-to-default.

Next, we observe that General CSI particularly influences the stock performance of highly levered banks. During the crisis years, individual crisis sentiment had a differential effect on banks with high and low leverage ratios and affected the respective stock performance negatively as well. Also, we find no clear evidence that crisis sentiment affects banks with higher or lower market-to-book ratio differently. The variable CSI is only slightly significant in the regressions for the period from 2006 to 2010.

Finally, we observe that the effect of General CSI on bank stock performance is also different for banks with different exposures to systemic risk. In the first quartile of MES (bank stocks that are insensitive to external shocks), bank stock performance is negatively affected by market-wide crisis sentiment while highly exposed banks did not suffer from such influence. This finding is in line with the notion of investors differentiating between systemically relevant and irrelevant banks. More precisely, it seems as if crisis sentiment is particularly important in the absence of implicit government bailouts with the effect of crisis sentiment being strongest for those banks that are least likely to receive a bailout.

3.3 Are banks a special case?

The question arises whether banks represent a special case when examining the influence of crisis sentiment on their equity prices. In general, banks differ from, e.g., industrial companies in several ways such as their business model, their average level of total assets, or simply their interconnectedness with large parts of the real economy. Also, as the financial crisis originated in the banking sector, it could be assumed that especially irrational noise traders associate the equities of banks with the crisis. Although banks face a whole set of additional financial risks, they also benefit from their importance for the economy and thus, explicit or implicit bailout guarantees. The literature provides empirical evidence that, e.g., the sheer size may be a decisive factor for investors to pursue investment opportunities with a bank (see, e.g., Oliveira et al., 2014; Demirgüç-Kunt and Huizinga, 2013). Recent studies also find that possible "too-big-to-fail" perceptions or government interventions have a strong effect on equity prices and the credit risk of banks, which cannot be found among non-financial firms (see, e.g., Gandhi and Lustig, 2015; Schweikhard and Tsesmelidakis, 2011).

Consequently, we are interested in whether crisis sentiment affects non-financial companies' stocks in a different way than it influences banks' stock performance. Therefore, we estimate separate panel regressions for our banking sample for the full sample period and also for the period from 2006 to 2010 and compare the results and the economic significance of crisis sentiment for bank stock performance with respective results from regressions with a sample of global non-financial firms.[8] The regression results are given in Table VII.

— insert Table VII here —

First, we can observe that size and stock performance are negatively related while profitability (Return on assets) increases returns for both banks and non-financial companies. The regressions that include the idiosyncratic crisis sentiment index again show that, over the full sample, we do not find a significant influence of this individual measure. This holds true for banks and

[8] The international sample of non-financial companies consists of 756 listed firms and is build from the constituents of the S&P Global 1200 index (see Section 2.2.2 for the construction of the final list.)

non-financial firms as well. However, looking at the coefficients of our General Crisis Sentiment Index reveals an interesting pattern. Although increased market-wide sentiment seems to decrease stock performance for the whole time period and for the crisis years, we observe a differentiation made by investors between banks and non-financial companies. A one-standard deviation increase in the crisis sentiment variable for the whole time period decreases bank stock returns by -2.1% (-0.0022×9.4753) while non-financial stock returns decrease by -6.0% (-0.0063×9.4753). Consequently, the sample of non-financial companies suffered to a larger extent from crisis sentiment than banks.

Restricting the time frame to the period from 2006 to 2010 and thus, concentrating on the time of the financial crisis yields an even more interesting finding. Generally, we would expect that the impact of crisis sentiment on stock performance is strongest around the times of financial market turmoil. For banks, however, we find the reversed effect since an increase of one standard deviation in crisis sentiment during this shorter time period results in a decrease of only -1.7% (-0.0014×12.0084). It therefore seems that although market-wide sentiment is high, bank stocks did not suffer from irrational investor behavior in a higher magnitude. In contrast, the economic significance of increased sentiment for non-financial companies' stock returns is -8.8% (-0.0073×12.0084) and thus, higher during the crisis years.

We conclude that bank stocks indeed represent a special case when examining the impact of market-wide crisis sentiment on their returns. Again, this finding is most consistent with the argument of Gandhi and Lustig (2015) that investors price implicit bailout guarantees into the equity prices of banks. Underlining our findings from Section 3.2 in which we found crisis sentiment to have the strongest effect on the stocks of banks with the smallest systemic relevance, we again find crisis sentiment to have a smaller effect on banks as a whole than on firms that are of no systemic relevance to the financial sector.

3.4 Robustness checks

In the previous analyses, we find that bank performance between January 2004 and December 2012 was significantly influenced by market-level crisis sentiment. The individual CSI, however, was only relevant for specific sub-groups of banks in our sample. Next, we estimate additional regressions including, e.g., country-specific factors to further explore the validity of our results. Also, we perform several tests to investigate the robustness of our results. Table VIII shows the results of further analyses and robustness checks.

— insert Table VIII here —

Columns (1) - (4) show the results of panel regressions similar to our baseline model using our full sample of banks but also include a country's GDP growth, inflation, and stock market turnover, as well as a variable representing the number of internet users per hundred people. In columns (5) - (8), we report the same regressions for banks in the fourth quartile of total assets.

As expected, the variable measuring the availability of internet access in a country enters the regressions with a negative sign. This is intuitive, since a higher proportion of internet users also indicates more or better information retrieval and thus, the possibility that negative sentiment influences the stock market to a larger extent. Also, we include the interaction term of internet usage and General CSI but find no evidence that it influences average bank stock returns.

Although General CSI and FEARS have a correlation of only 15%, we want to ensure that the General Crisis Sentiment Index is not captured in the FEARS index. Hence, we include both indices in regressions (2) - (3) and (6) - (7). The General CSI, again, is significant in these regressions. So is the FEARS index.

As another analysis, we include in our regressions (4) and (8) variables that describe the differences between countries' regulatory environments, but find no change in our main results.[9]

[9] Also, it could be interesting to see whether banks change some part of their business strategy in response to the effects of crisis sentiment, e.g., the way they derive their main income. Therefore, we run additional regressions using the ratio of a bank's non-interest income and its total interest income as our dependent variable and use crisis sentiment and bank fundamentals as our explanatory variables. These panel regressions, however, do not show any significant determinant among our set of variables.

In order to address concerns that crisis sentiment and buy-and-hold returns could be simultaneously determined, we lag all independent variables by one quarter. Despite using one-quarter lags one could still argue that, in our framework, persistence in our dependent variables might bias our estimates. We tackle this issue by modeling such persistence with a dynamic panel model and estimate our baseline models using the GMM-sys estimator (see Blundell and Bond, 1998). In this model, we include one lag of our dependent variable and use double-lagged values of the dependent variable, idiosyncratic CSI, and MES as instruments. Running the regressions with the GMM-sys estimator yields very similar results to our baseline model. Further, the General Crisis Sentiment Index remains highly significant and is negatively related to a bank's stock performance.

We also calculate our crisis sentiment measures with mean values instead of using a principal component analysis but find no relevant changes in our estimates. Our results, however, remain qualitatively unchanged.[10]

To address the concern that our crisis sentiment indices simply measure the overall volume of search queries on Google instead of the search queries for crisis-related terms, we calculate the General CSI and the CSI with arbitrary economic search terms. If the indices measured the overall volume of search queries, this alternative computation of the indices should lead to similarly significant results. As alternative search terms we use "consumer prices", "GDP", "economy", "emerging markets", "employment", "inflation", and "total assets". These search terms are not related to the financial crisis and do not carry a negative connotation. We calculate several indices which are constructed using these terms and replace our crisis sentiment indices in the panel regressions with them. In unreported regressions, we find that none of these placebo indices enter the regressions with a statistically significant coefficient.

Finally, to examine the predictive power of our measures of crisis sentiment, we perform several out-of-time forecasts within our sample period. We estimate our regressions for the subsamples Q2 2004-Q2 2006, Q1 2007-Q2 2008 and Q1 2007-Q4 2008 and predict the quarterly buy-and-

[10] To further ensure the robustness of our results, we employ slightly different proxies for some of our main variables, such as the log of net revenues as a proxy for size. Also, we calculate the Marginal Expected Shortfall using a different benchmark index (*MSCI World Banks Index* taken from *Datastream*). Our results remain unchanged.

hold returns in Q3 2006, Q4 2006, Q3 2008, Q4 2008, Q1 2009 and Q2 2009, respectively. The (unreported) results show that in the period before the financial crisis, the General CSI used in a univariate regression predicts the quarterly buy-and-hold returns with an average absolute prediction error in a bank's buy-and-hold return of less than 4%. During the crisis, we obtain better results for the prediction with the CSI and FEARS indices than with the General CSI. With the CSI, the banks' returns in Q3 2008 are forecasted with a mean average residual of about 4.5% across banks. Using the FEARS index leads to an even better forecast with mean absolute residuals being less than 4%. The prediction with the CSI and FEARS indices for the quarter directly after the financial crisis works even slightly better with an approximately 1% smaller mean absolute prediction error while the predictive power of the General CSI decreases to some extent during the crisis. In summary, we find all sentiment measures to have ample predictive power for the banks' stock returns with the predictive power increasing especially for the idiosyncratic CSI during the course of the financial crisis.

4 Conclusion

We examine the hypothesis that the stock performance of banks can, in part, be explained by the crisis sentiment of investors. In this paper, we investigate whether the losses experienced by bank stock investors were amplified by irrational market-wide and firm-individual crisis sentiment. We employ three measures of crisis sentiment in our analysis to test this assumption. First, we calculate the CSI developed by Weiß et al. (2013) as a proxy for idiosyncratic crisis sentiment. Next, we compute the General Crisis Sentiment Index of Weiß et al. (2013) and the FEARS index of Da et al. (2015) as a measure of market-level crisis sentiment.

In our panel regressions of banks' quarterly buy-and-hold returns, we find convincing evidence that the performance of banks during the period from January 2004 to December 2012 was indeed driven by investors' irrational market-wide crisis sentiment. The FEARS index supports the results obtained with the General Crisis Sentiment Index. In contrast, we find that idiosyncratic crisis sentiment did not have a significant impact on bank stock performance during our complete sample period regardless of a bank's size. The effects of market-wide sentiment on bank stock performance are economically large and hold in a battery of robustness tests. Analyzing the economic impact of crisis sentiment on the stock returns of systemically and non-systemically relevant banks as well as non-financial companies reveals that the effect of crisis sentiment is even stronger for stocks of non-financial companies and banks of low systemic importance. These findings support the notion that crisis sentiment has a stronger effect in the absence of bailout guarantees supporting the findings of, e.g., Gandhi and Lustig (2015).

A Appendix

Appendix A.1: Sample banks.

This table lists all banks that are used in our empirical study. The sample consists of 413 international banks with SIC Codes 6011, 6021, 6022, 6029, 6035, 6036, and 6141, for which stock price and balance sheet data are available from *Thomson Reuters Financial Datastream* and *Worldscope*. The names of the banks are retrieved from the *Worldscope* database (WC06001).

AAREAL BANK AG	CRCAM ATLANTIQUE	MIYAZAKI BANK LTD.
ABN AMRO HOLDING	CRCAM NORD DE	MIZRAHI TEFAHOT
ABU DHABI COMMERCIA	CREDICORP LTD.	MIZUHO FINANCIAL GRP
ACOM CO., LTD.	CREDIT AGRICOLE SA	MUSASHINO BANK, LTD.
AGRI BANK OF GREECE	CREDIT INDUSTRIEL	N Y COMMUNITY
AHLI UNITED BANK BSC	CREDIT SAISON CO.	NANTO BANK, LTD.
AICHI BANK, LTD.	CREDITO BERGAMASCO	NATIONAL BANK
AIFUL CORP	CREDITO E INVERSION	NATIONAL BANK/CANADA
AKBANK TAS	CREDITO EMILIANO SPA	NATIONAL CITY CORP
AKITA BANK, LTD.	CTBC FINANCIAL HOLD	NATIXIS
AL RAJHI BANK	CULLEN/FROST BANKERS	NAT'L AUSTRALIA BANK
ALLIED IRISH BANKS	CYPRUS POPULAR BANK	NATL BANK OF GREECE
ALPHA BANK A.E.	DAH SING FINANCIAL	NATL BK OF PAKISTAN
AMMB HOLDINGS BERHAD	DAISAN BANK LTD.	NELNET, INC.
ANGLO IRISH BANKCORP	DAISHI BANK, LTD.	NEUE AARGAUER BANK
AOMORI BANK, LTD.	DANSKE BANK A/S	NISHI-NIPPON CITY
AOZORA BANK LTD.	DBS GROUP HOLDINGS	NORDEA BANK
ARAB BANK GROUP	DENIZBANK	NORTH PACIFIC BANK
ARAB BANKING CORP	DEUTSCHE BANK AG	NORTHERN ROCK PLC
ARAB NATIONAL BANK	DEUTSCHE HYPOTHEKENBANK	NORTHERN TRUST CORP
ASSOCIATED BANC-CORP	DEUTSCHE POSTBANK AG	OBERBANK AG
ASTORIA FINANCIAL	DEXIA SA	OEST. VOLKSBANKEN-AG
ATTIJARIWAFA BANK	DGB FINANCIAL	OGAKI KYORITSU BANK
AUSTRALIA & NZ BANK	DISCOVER FINANCI	OITA BANK, LTD.
AWA BANK, LTD.	DNB ASA	OLDENBURGISCHE L-BK
AXIS BANK	DORAL FINANCIAL CORP	ORIENT CORP
BANCA CARIGE	DUBAI ISLAMIC BANK	ORIENTAL BANK OF COM
BANCA MONTE PASCHI	DVB BANK SE	OTP BANK NYRT
BANCA PICCOLO	E SUN FINANCIAL HLDG	OVERSEA-CHINESE
BANCA POP DI MILANO	E*TRADE FINANCIAL	PARAGON GROUP
BANCA POPOLARE	EAST WEST BANCORP	PEOPLE'S UNITED
BANCA POPOLARE DELL	ECOBANK NIGERIA PLC	PING AN BANK
BANCO BILBAO VIZCAYA	EFG INTERNATIONAL	PIRAEUS BANK
BANCO BPI, S.A.	EHIME BANK, LTD.	PNC FINANCIAL SERVICES GRP
BANCO COMERCIAL PORT	EIGHTEENTH BANK LTD.	POHJOLA BANK
BANCO DE ANDALUCIA	EMIRATES NBD	POPULAR, INC.
BANCO DE CHILE	EMPORIKI BANK OF GR	POWSZECHNA KASA
BANCO DE VALENCIA SA	EON CAPITAL BHD	PT BANK MANDIRI
BANCO DI SARDEGNA	ERSTE GROUP BANK AG	PT BANK RAKYAT
BANCO DO BRASIL S.A.	ESPIRITO SANTO FINANCIAL	PUBLIC BANK BHD
BANCO ESP DE CREDITO	EUROBANK ERGASIAS SA	PUNJAB NATIONAL BANK
BANCO ESPIRITO SANTO	FAR EASTERN INT'L BK	QATAR NATIONAL BANK
BANCO GUIPUZCOANO SA	FIFTH THIRD BANCORP	RAIFFEISEN BANK
BANCO NOSSA	FINANSBANK	REGIONS FINANCIAL
BANCO PASTOR S.A.	FIRST BANCORP	RESONA HOLDINGS INC

Appendix A.1: Sample banks (continued).

BANCO POPOLARE	FIRST CITIZENS BANC	RHB CAPITAL BERHAD
BANCO POPULAR ESP.	FIRST FINANCIAL HOLDING CO	RIYAD BANK
BANCO SABADELL	FIRST GULF BANK	ROSBANK OAO
BANCO SANTANDER	FIRST HORIZON NATL	ROYAL BANK
BANCO SANTANDER SA	FIRST INTL BK OF ISR	ROYAL BANK OF CANADA
BANCOLOMBIA S.A.	FIRSTMERIT CORP	SAMBA FINANCIAL
BANCORPSOUTH INC	FIRSTRAND LIMITED	SAN-IN GODO BANK
BANGKOK BANK LIMITED	FLAGSTAR BANCORP INC	SANTANDER MEXICO
BANK AUDI SAL	FUKUI BANK, LTD.	SAUDI BRITISH BANK
BANK BPH S.A.	FULTON FINANCIAL CORP	SAUDI INVESTMENT
BANK CENTRAL ASIA	GRAUBUENDNER KBK	SBERBANK ROSSII
BANK HANDLOWY	GRUPO AVAL ACCIONES	SCHWEIZERISCHE NATL
BANK HAPOALIM B.M.	GRUPO FINANCIERO BANORTE	SCIB PCL
BANK LEUMI LE-ISRAEL	GULF BANK OF KUWAIT	SENSHU BANK, LTD.
BANK NEGARA	GUNMA BANK, LTD.	SEVENTY-SEVEN BANK
BANK OF AMERICA CORP	HACHIJUNI BANK, LTD.	SHANGHAI PUDONG
BANK OF AYUDHYA PCL	HACI OMER SABANCI	SHIGA BANK, LTD.
BANK OF BARODA	HANA FINANCIAL GROUP	SHIKOKU BANK LTD.
BANK OF BEIJING CO	HANG SENG BANK LTD.	SHIMIZU BANK, LTD.
BANK OF CHINA LTD.	HBOS PLC	SHINHAN FINANCIAL GR
BANK OF COMMN	HDFC BANK LIMITED	SHINSEI BANK LTD.
BANK OF EAST ASIA	HIGASHI-NIPPON BANK	SHIZUOKA BANK, LTD.
BANK OF GREECE SA	HIGO BANK, LTD.	SIAM COMMERCIAL
BANK OF HAWAII CORP	HIROSHIMA BANK, LTD.	SINOPAC FINANCIAL HOLDINGS
BANK OF IKEDA, LTD.	HITACHI CAPITAL CORP	SKANDINAVISKA ENSK
BANK OF INDIA	HOKKOKU BANK LTD.	SLM CORPORATION
BANK OF IRELAND	HOKUETSU BANK	SOCIEDAD MATRIZ
BANK OF IWATE, LTD.	HONG LEONG BANK BHD	SOVEREIGN BANCORP
BANK OF KYOTO, LTD.	HONG LEONG FINANCIAL	SPAREBANK 1 SR BANK
BANK OF MONTREAL	HOUSING DEVELOPMENT	ST GALLER KANTON
BANK OF MOSCOW	HSBC HOLDINGS PLC	ST. GEORGE BANK LTD.
BANK OF NAGOYA, LTD.	HSBC TRINKAUS & BURK	STANDARD BANK GRP
BANK OF NEW YORK	HUA NAN FINANCIAL	STANDARD CHARTERED
BANK OF NOVA SCOTIA	HUA XIA BANK COMPANY	STATE BANK OF INDIA
BANK OF OKINAWA, LTD.	HUDSON CITY BANCORP	STATE STREET CORP
BANK OF QUEENSLAND	HUNTINGTON BANCSHR	STE. GENL. DE FRANCE
BANK OF SAGA LTD.	HYAKUGO BANK, LTD.	SUMI MITSUI FINANCIAL GRP
BANK OF THE PHIL.	HYAKUJUSHI BANK LTD.	SUMITOMO TRUST/BANK.
BANK OF THE RYUKYUS	HYPO REAL ESTATE	SUNTRUST BANKS INC
BANK OF YOKOHAMA	ICICI BANK LIMITED	SURUGA BANK, LTD.
BANK PEKAO S.A.	IDBI BANK LTD.	SV. HANDELSBANKEN AB
BANK ZACHODNI WBK SA	IKB BANK	SWEDBANK AB
BANKINTER S.A.	IND BANK OF KOREA	SYDBANK A/S
BANQUE CANT VAUDOISE	INDIAN BANK	SYNDICATE BANK
BANQUE NATL BELGIQUE	INDIAN OVERSEAS BANK	SYNOVUS FINANCIAL
BANQUE SAUDI FRANSI	INDUST'L & COMMERC'L	TA CHONG BANK
BARCLAYS AFRIC	INDUSTRIAL BANK	TAIKO BANK LTD.
BARCLAYS PLC	ING BANK SLASKI SA	TAISHIN FINANCIAL
BASELLAND KANTONALBK	INTESA SANPAOLO SPA	TAIWAN BUSINESS

Appendix A.1: Sample banks (continued).

BASLER KANTONALBANK	INT'L BANCSHARES	TAIWAN COOPERATIVE
BAYER. HYPO- UND VEREINSBANK	ISRAEL DISCOUNT BANK	TCF FINANCIAL CORP
BB&T CORPORATION	IYO BANK LTD.	THE SOUTH FINANCIAL GRP
BERLIN-HANNOVERSCHE	JACCS CO., LTD.	TMB BANK PCL
BERNER KANTO	JAPAN SEC FINANCE	TOCHIGI BANK, LTD.
BK AUSTRIA CREDITAN	JOINT ST CO BANK	TOHO BANK, LTD.
BLOM BANK SAL	JOYO BANK, LTD.	TOKYO TOMIN BANK LTD.
BNP PARIBAS	JPMORGAN CHASE & CO	TORONTO-DOMINION BNK
BOK FINANCIAL CORP	JULIUS BAER	TOWA BANK, LTD.
BRADFORD & BINGLEY	JUROKU BANK, LTD.	TSUKUBA BANK
BS FINANCIAL	JYSKE BANK A/S	TURKIYE GARANTI BANK
BTA BANK AO	KAGAWA BANK, LTD.	TURKIYE HALK BANKASI
C.A. ILE DE FRANCE	KAGOSHIMA BANK, LTD.	TURKIYE IS BANKASI
C.AGR. CENTRE LOIRE	KANSAI URBAN	TURKIYE VAKIFLAR
CA ALPES PROVENCE	KASIKORNBANK PLC	U. S. BANCORP
CA SUD RHONE ALPES	KAZKOMMERTSBANK	UBI BANCA
CAISSE REG DE CREDIT	KB FINANCIAL GROUP	UBS AG
CAISSE REGIONALE DE	KBC GROUP NV	UCO BANK LTD.
CAIXABANK	KEIYO BANK, LTD.	UNIBANCO HOLDINGS SA
CANADIAN IMPERIAL	KEYCORP	UNICREDIT SPA
CANARA BANK	KIYO HOLDINGS, INC	UNION BANK OF INDIA
CAPITAL ONE FINANCIAL	KOMERCNI BANKA, A.S.	UNION BANK OF TAIWAN
CAPITALSOURCE INC	KOREA EXCHANGE BANK	UNION NATIONAL BANK
CENTRAL BANK	KRUNG THAI BANK PCL	UNIONBANCAL CORP
CENTRAL FINANCE CO.	KUWAIT FINANCE HOUSE	UNITED OVERSEAS BANK
CHANG HWA BANK	LANDESBANK BERLIN	VALIANT HOLDING
CHIBA BANK, LTD.	LANDSBANKI ISLANDS	VALLEY NATIONAL BANC
CHIBA KOGYO BANK	LIECHTENSTEIN LANDBK	VAN LANSCHOT NV
CHINA CITIC BANK	LLOYDS BANKING GROUP	VORARLBERGER BANK AG
CHINA CONSN	LUZERNER KANTONAL	WACHOVIA CORP
CHINA MERCHANTS BANK	M&T BANK CORPORATION	WEBSTER FINANCIAL CORP
CHINA MINSHENG BANK	MAF BANCORP, INC.	WELLS FARGO & CO
CHUGOKU BANK, LTD.	MALAYAN BANKING BHD	WESTPAC BANKING CORP
CHUKYO BANK, LIMITED	MARSHALL & ILSLEY	WHITNEY HOLDING CORP
CIMB GROUP HOLDIN	MASHREQ BANK	WILMINGTON TRST
CITIC INTERNATIONAL	MBANK	WOORI FINANCE HOLD
CITIGROUP INC	MEDIOBANCA SPA	YACHIYO BANK
CITIZENS REPUBLIC	MEGA FINANCIAL	YAMAGATA BANK, LTD.
CITY NATIONAL CORP	MERCANTIL SERVICIOS	YAMANASHI CHUO BANK
COMERICA INC.	METROPOLITAN BANK	YAPI VE KREDI
COMMERCE BANCORP INC	MICHINOKU BANK, LTD.	YUANTA FINANCIAL
COMMERCE BANCSHARES	MIE BANK, LTD.	ZAGREBACKA BANKA
COMMERZBANK AG	MINATO BANK, LTD.	ZIONS BANCORPORATION
CRCAM AQUITAINE	MITSUBISHI UFJ	

Appendix A.2: Variable definitions and data sources.

The table presents definitions and data sources for all dependent and independent variables that are used in the empirical study. *Datastream* mnemonics are given in parentheses.

Variable name	*Definition*	*Data source*
Panel A: Dependent variable		
Buy-and-hold returns	Quarterly buy-and-hold returns on a bank's stock.	Datastream, own calc.
Panel B: Main explanatory variables		
General Crisis Sentiment Index (General CSI)	First principle component of the four GSVIs of the search terms "financial crisis", "credit crisis", "subprime crisis", and "bank crisis". It is calculated with a rolling window enlarged by one week after each estimation, starting with a window of 52 weeks for the first year. For each quarter, the average of the weekly first principle component is computed.	Google Trends, own calc.
Crisis Sentiment Index (CSI)	The CSI for bank i at time t is defined as $CSI_t^i := (GSVI_t^i + Z_t)/200 \cdot \rho_t^i$, where $GSVI_t^i$ is the Google Search Volume Index (GSVI) for the i-th bank's ticker symbol or company name, Z_t is the first principle component of the GSVI for four crisis-related search terms and ρ_t^i is the correlation between Z_t and $GSVI_t^i$.	Datastream, Google Trends, own calc.
FEARS	The FEARS index is defined as $FEARS_t = \frac{1}{30}\sum_{j=1}^{30} \Delta AGSVI_t^j$, where $\Delta AGSVI_t^j$ is the adjusted weekly change in search term j. The search terms used to compute the index are listed in Appendix A.3.	Google Trends, own calc.
Panel C: Control variables		
Bank characteristics		
Size	Natural logarithm of a bank's total assets.	Worldscope (WC02999).
Return on assets	The pre-tax return of a bank on its total assets.	Worldscope (WC08326).
Distance-to-default	Natural logarithm of the z-score. Z-score is the sum of a bank's return on assets and a bank's equity to assets ratio, scaled by the standard deviation of return on assets over a five-year window (see Anginer et al., 2014).	Worldscope (WC08326, WC03501, WC02999), own calc.
MES	The negative average return on a bank's stock calculated on the days the market experienced its 5% worst outcomes.	Datastream, own calc.
Market-to-book	Market value of common equity divided by book value of common equity.	Worldscope (WC07210 and WC03501).
Leverage	Book value of assets minus book value of equity plus market value of equity, divided by market value of equity (see Acharya et al., 2010).	Worldscope (WC02999, WC03501, WC07210), own calc.
Loans	Ratio of total loans to total assets.	Worldscope (WC02271 and WC07230).

Appendix A.2: Variable definitions and data sources (continued).

Variable name	*Definition*	*Data source*
Non-interest income	Ratio of non-interest income to the sum of non-interest income and net interest income.	Worldscope (WC01021 and WC01076), own calc.
Net revenues	Natural logarithm of a bank's net revenues.	Worldscope (WC07240).
Tier 1 capital	Tier 1 capital ratio as reported in the Worldscope database.	Worldscope (WC18157).
Macroeconomic control variables		
GDP growth	Annual real GDP growth rate (in %).	WDI database.
Inflation	Log of the annual change of the GDP deflator.	WDI database.
Internet use	Number of internet users in a bank's home country per 100 people.	WDI database.
Stock market turnover	Ratio of annual trading volume to shares outstanding.	WDI database.
Regulatory control variables		
Supervisory power index	The degree to which official supervisory authorities are allowed to take specific actions to prevent and correct unwelcome events. Index ranges from 0 to 14. Higher scores denote greater power.	Barth et al. (2006, 2013).
Capital regulatory index	The degree to which the capital requirement reflects certain risk elements and to which certain funds may be used to initially capitalize a bank. Index ranges from 0 to 10. Higher values denote greater stringency.	Barth et al. (2006, 2013).
Restrictions on bank activities index	The extent to which banks are restricted in their activities in securities markets, insurance and real estate activities, and owning shares in non-financial firms. Index ranges from 4 to 16. Higher scores denote greater restrictiveness.	Barth et al. (2006, 2013).
Independence of supervisors index	A measure for the supervisory authority's independence from the government and its legal protection from the banking industry. Index ranges from 0 to 3. Higher scores denote greater independence.	Barth et al. (2006, 2013).
Deposit insurance	Dummy variable taking on the value one if a country has an explicit deposit insurance scheme and zero otherwise.	Barth et al. (2006, 2013).

Appendix A.3: FEARS search terms.

This table presents the thirty search terms used to compute the FEARS index as proposed by Da et al. (2015).

GOLD PRICES	FRUGAL	EXPENSE
RECESSION	GDP	DONATION
GOLD PRICE	CHARITY	SAVINGS
DEPRESSION	BANKRUPTCY	SOCIAL SECURITY CARD
GREAT DEPRESSION	UNEMPLOYMENT	THE CRISIS
GOLD	INFLATION RATE	DEFAULT
ECONOMY	BANKRUPT	BENEFITS
PRICE OF GOLD	THE GREAT DEPRESSION	UNEMPLOYED
THE DEPRESSION	CAR DONATE	POVERTY
CRISIS	CAPITALIZATION	SOCIAL SECURITY OFFICE

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Tables and Figures

Figure 1: Illustration of Google search volume.

The figure presents the graphical output of the weekly Google Search Volume Index of the search term "subprime crisis" from *Google Trends*. The GSVI is the daily or weekly search volume for a chosen period scaled by the period's maximum.

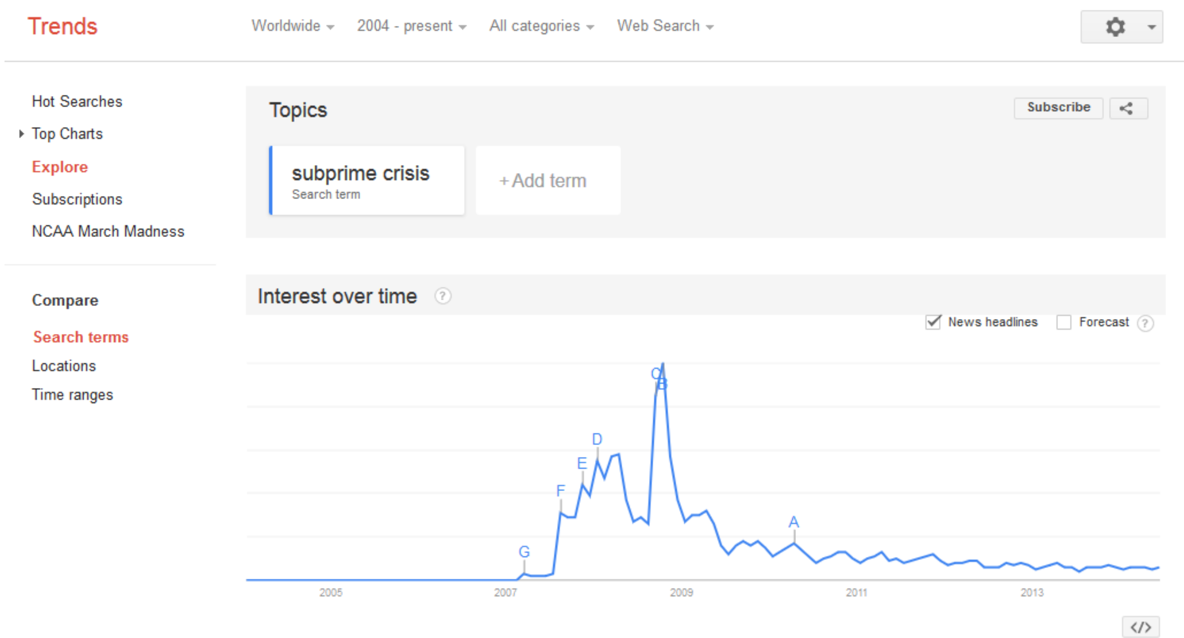


Figure 2: Google Search Volume Indices for crisis-related search terms.

The figure shows the time evolution of the General crisis sentiment index measured as the first principal component of the four search terms “financial crisis”, “credit crisis”, “bank crisis”, and “subprime crisis”, and the time evolution of the GSVIs for these search terms for the time period from January 2004 to December 2012.

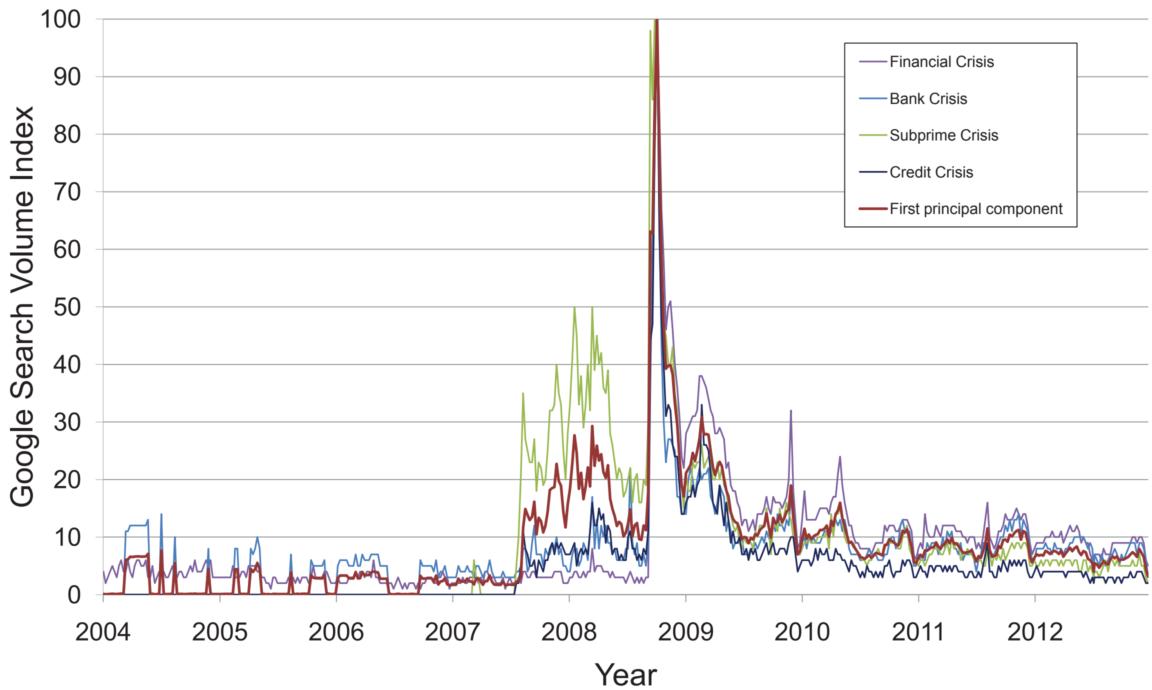
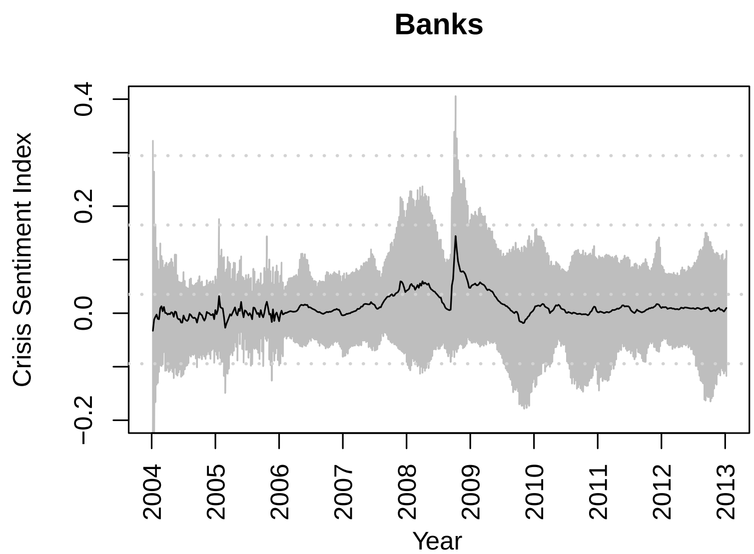


Figure 3: Time evolution of the Crisis Sentiment Index.

The figure shows a plot of the evolution of the Crisis Sentiment Index across our sample of 254 banks and 756 non-financial firms over our sample period from 2004 to 2012. The CSI for firm i at time t is defined as $CSI_t^i := (GSVI_t^i + Z_t)/200 \cdot \rho_t^i$, where $GSVI_t^i$ is the Google Search Volume Index for the i-th firm's ticker symbol or company name, Z_t is the first principle component of the GSVI for four crisis-related search terms, and ρ_t^i is the correlation between Z_t and $GSVI_t^i$. The solid line shows the mean values of CSI across the sample. The area shaded in grey shows the range between the empirical 10%- and 90% quantiles, which are computed separately for each point of time.



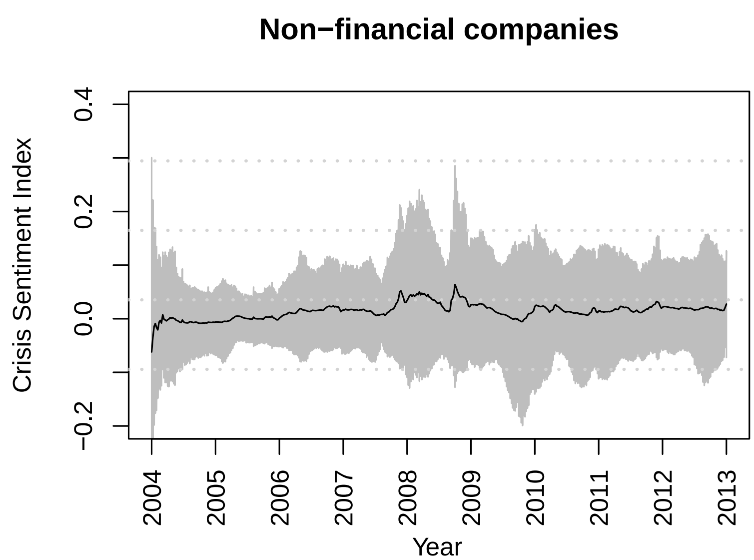


Figure 4: Crisis sentiment and bank stock prices.

The figures show the time evolution of the individual CSI values of Citigroup, JP Morgan Chase, BNP Paribas, and HSBC as well as their respective stock prices from January 2004 to December 2012. The CSI for bank i at time t is defined as $CSI_t^i := (GSVI_t^i + Z_t)/200 \cdot \rho_t^i$, where $GSVI_t^i$ is the Google Search Volume Index for the i-th bank's ticker symbol or company name, Z_t is the first principle component of the GSVI for four crisis-related search terms and ρ_t^i is the correlation between Z_t and $GSVI_t^i$.

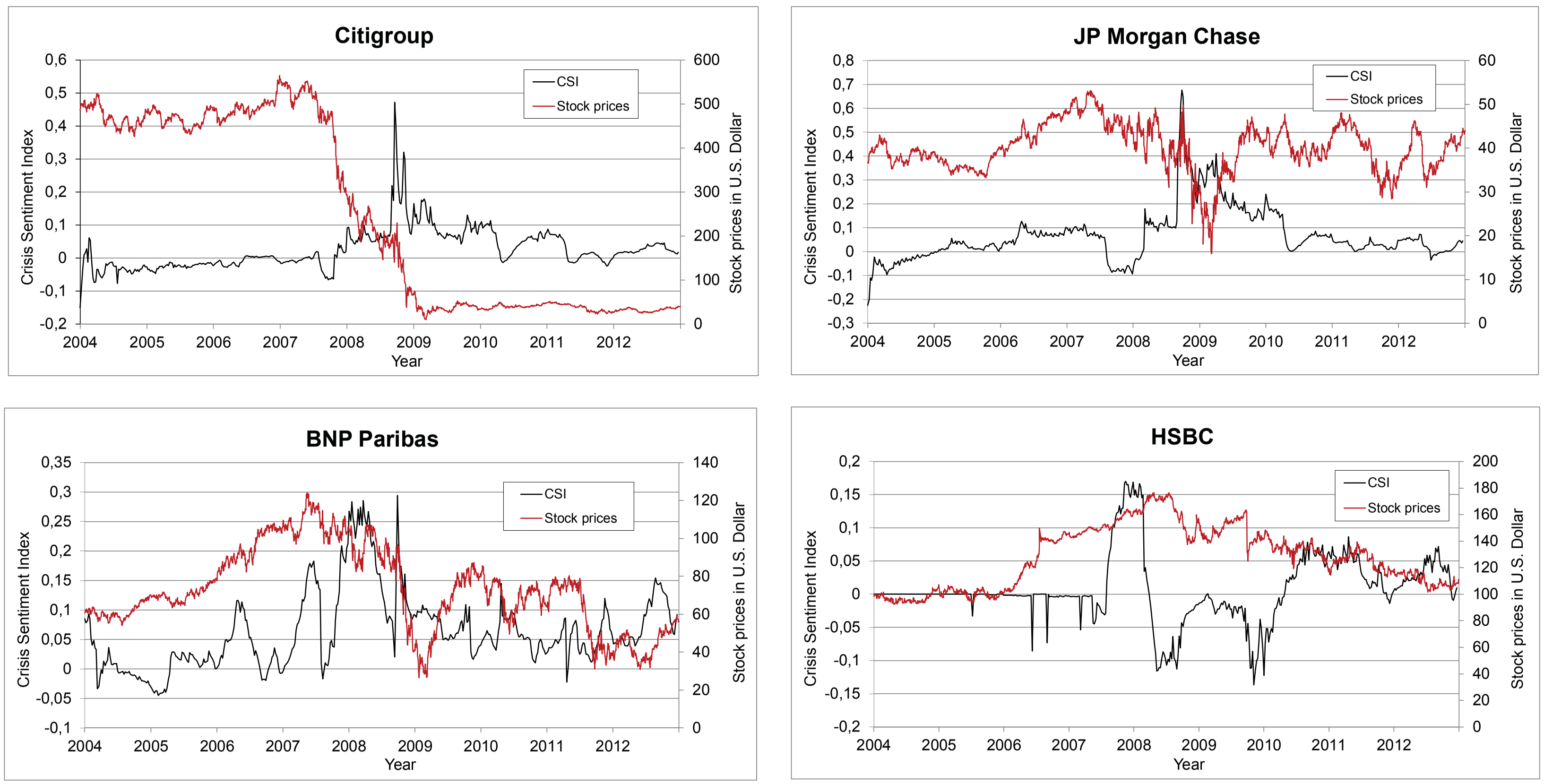


Figure 5: Time evolution of the FEARS index.

The figure shows a plot of the quarterly time evolution of the FEARS index over our sample period from 2004 to 2012. The FEARS index is defined as $FEARS_t := \frac{1}{30}\sum_{j=1}^{30} \Delta AGSVI_t^j$, where $\Delta AGSVI_t^j$ is the adjusted weekly change in the Google Search Volume Index for search term j. The search terms used to compute the index are listed in Appendix A.3.

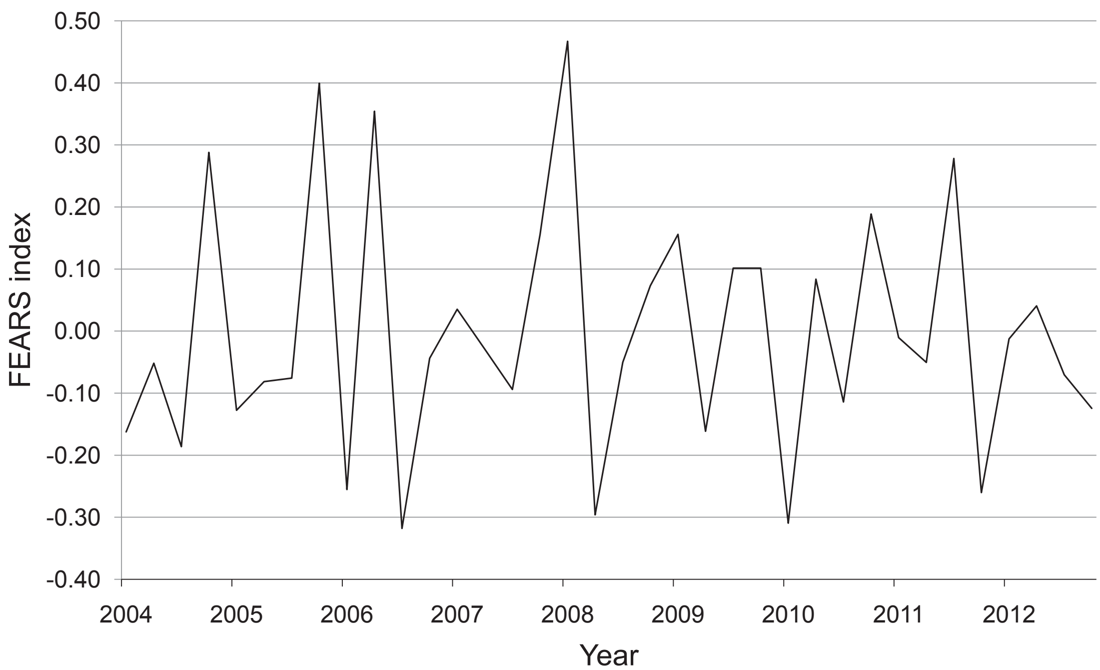


Table I: Descriptive statistics.

The table presents descriptive statistics on quarterly buy-and-hold returns and on all variables used in the empirical study. The statistics are shown for our sample of 413 banks for the period from Q1 2004 to Q4 2012. Bank characteristics are given on a quarterly basis, whereas macroeconomic and regulatory control variables are only available on a yearly basis. Total assets are given in $ billion. We report the number of observations, mean and median values, 5%- and 95% quantiles, minimum and maximum values as well as the standard deviation. The variables and their data sources are defined in Appendix A.2.

	Observations	Mean	5% quantile	Median	95% quantile	Min	Max	St. Dev.
Bank performance and main explanatory variables								
Buy-and-hold returns	14,868	-0.020	-0.354	0.000	0.229	-1.000	0.478	0.183
CSI	8,182	0.014	-0.109	0.007	0.149	-0.334	0.523	0.078
General crisis sentiment	36	8.965	0.407	7.428	24.748	0.333	48.386	9.359
FEARS	36	-0.001	-0.309	-0.044	0.399	-0.318	0.467	0.197
Control variables								
Total assets	14,868	161.646	11.120	38.199	816.429	0.505	4,766.854	392.742
Return on assets	13,027	1.115	-0.290	1.070	3.170	-20.260	19.960	1.506
MES	14,021	0.008	-0.003	0.005	0.026	-0.075	0.127	0.010
Market-to-book	13,561	1.602	0.356	1.260	3.686	-18.201	183.265	3.434
Leverage	13,561	25.659	3.637	12.511	59.547	1.334	4,725.266	122.230
Non-interest income	13,698	0.386	0.136	0.362	0.705	-3.327	8.607	0.274
Loans	13,497	0.664	0.396	0.675	0.879	0.000	1.639	0.151
Distance-to-default	12,010	1.084	-1.001	1.262	2.723	-24.980	5.848	1.427
Tier 1 capital	10,574	10.875	6.300	9.960	17.350	-7.300	125.840	6.550
GDP growth	14,868	2.733	-3.832	2.507	9.285	-8.539	33.736	3.687
Inflation	14,868	2.910	-1.352	2.208	11.015	-18.932	27.568	4.339
Internet use	14,868	58.186	7.500	67.968	83.900	1.286	96.000	24.056
Stock market turnover	14,868	119.182	21.325	114.488	229.609	0.000	404.067	72.415

Table II: Descriptive statistics before, during, and after the crisis.

The table presents descriptive statistics on quarterly buy-and-hold returns and on selected variables used in the empirical study. The statistics are shown for our sample of 413 banks for time periods before, during, and after the financial crisis. Bank characteristics are given on a quarterly basis, whereas macroeconomic and regulatory control variables are only available on a yearly basis. Total assets are given in $ billion. We report the number of observations, mean and median values, 5%- and 95% quantiles, minimum and maximum values as well as the standard deviation. The variables and their data sources are defined in Appendix A.2.

	Observations	Mean	5%-quantile	Median	95%-quantile	Min	Max	St. Dev.
Q2 2004 - Q2 2007 (pre-crisis)								
Buy-and-hold returns	5,020	0.0227	-0.1814	0.0234	0.2263	-0.9083	0.4523	0.1264
CSI	2,500	0.0005	-0.0801	0.0003	0.0838	-0.3235	0.2273	0.0497
General crisis sentiment	5,369	1.7573	0.3331	1.6856	4.1513	0.3331	4.1513	1.1116
FEARS	5,369	-0.0174	-0.3179	-0.0759	0.3993	-0.3179	0.3993	0.2194
MES	4,998	0.0053	-0.0024	0.0042	0.0175	-0.0177	0.0843	0.0063
Leverage	5,090	14.3266	2.9831	9.3819	27.7870	1.3344	977.0728	42.2217
Distance to default	4,521	1.3125	-0.7119	1.4655	2.9203	-21.8051	5.8478	1.2864
Q3 2007 - Q4 2008 (crisis)								
Buy-and-hold returns	2,444	-0.1209	-0.5438	-0.0823	0.1854	-1.0000	0.4778	0.2218
CSI	1,385	0.0340	-0.0926	0.0241	0.1975	-0.2667	0.4453	0.0860
General crisis sentiment	2,478	14.1567	2.0653	16.7665	21.2696	2.0653	21.2696	6.8391
FEARS	2,478	0.0254	-0.2962	-0.0399	0.4670	-0.2962	0.4670	0.2375
MES	2,478	0.0083	-0.0035	0.0062	0.0278	-0.0153	0.1273	0.0111
Leverage	2,408	26.5993	3.6035	14.0407	70.6219	1.5728	2,034.7405	82.3421
Distance to default	2,049	1.1941	-1.0642	1.3680	2.7774	-18.7692	5.6851	1.6130
Q1 2009 - Q4 2012 (post-crisis)								
Buy-and-hold returns	6,575	-0.0141	-0.3578	0.0008	0.2455	-1.0000	0.4778	0.1902
CSI	3,884	0.0159	-0.1327	0.0133	0.1583	-0.3335	0.5227	0.0868
General crisis sentiment	6,608	12.8745	5.7138	9.5968	48.3862	5.7138	48.3862	10.2695
FEARS	6,608	0.0021	-0.3094	0.0150	0.2780	-0.3094	0.2780	0.1545
MES	6,583	0.0098	-0.0023	0.0068	0.0318	-0.0753	0.1198	0.0114
Leverage	6,028	34.2190	4.3971	15.9402	75.0065	1.6247	4,721.3759	168.3158
Distance to default	5,027	0.8346	-1.2082	1.0192	2.4625	-24.9800	4.9628	1.4277

Table III: Descriptive statistics for bank-quarters in the first and fourth crisis sentiment quartile.

The table presents descriptive statistics on buy-and-hold returns and on all independent variables for bank-quarters in the bottom quartile and top quartile of the CSI. The statistics are shown for the sample of 337 banks for which the Google Search Volume indices are available for the period from Q1 2004 to Q4 2012. Bank characteristics are given on a quarterly basis, whereas macroeconomic and regulatory control variables are only available at a yearly frequency. We report mean values, 5%- and 95% quantiles as well as the standard deviation. The variables and their data sources are defined in Appendix A.2. To test the equality of means, we perform t-tests and report corresponding p-values. ***,**, and * denote significance at the 1%, 5% and 10% level, respectively.

	Bottom crisis sentiment quartile				Top crisis sentiment quartile				
	Mean	5% quantile	95% quantile	St. Dev.	Mean	5% quantile	95% quantile	St. Dev.	t-Test
Bank performance and main explanatory variables									
Buy-and-hold returns	-0.037	-0.447	0.244	0.253	-0.087	-0.639	0.286	0.608	0.000***
CSI	-0.094	-0.226	-0.034	0.064	0.124	0.057	0.263	0.074	0.000***
General crisis sentiment	9.925	0.777	24.748	8.631	13.687	1.540	48.386	11.585	0.000***
FEARS	0.006	-0.309	0.354	0.189	0.008	-0.309	0.399	0.195	0.653
Control variables									
Total assets	7.838	7.109	9.098	0.580	7.867	7.089	9.187	0.616	0.110
Return on assets	1.150	-0.380	3.230	1.690	1.116	-0.739	2.880	1.411	0.501
MES	0.009	-0.001	0.029	0.011	0.012	-0.002	0.041	0.015	0.000***
Market-to-book	1.591	0.335	3.632	1.567	1.418	0.251	3.402	1.235	0.000***
Leverage	34.014	3.629	58.805	230.067	31.847	3.775	79.318	145.347	0.715
Non-interest income	0.411	0.163	0.725	0.170	0.415	0.147	0.726	0.324	0.567
Loans	0.665	0.394	0.886	0.157	0.656	0.358	0.875	0.161	0.064*
Distance-to-default	1.085	-0.983	2.869	1.763	1.139	-0.787	2.777	1.602	0.337
Tier 1 capital	10.838	6.734	16.600	3.473	10.823	6.408	16.660	3.510	0.898
Internet use	58.043	9.000	85.200	23.736	61.045	10.070	85.020	22.181	0.000***

Table IV: Mean buy-and-hold returns for bank-quarters in quintiles of total assets, MES, and CSI.

The table presents a comparison of the average buy-and-hold returns for bank-quarters sorted by quintiles of total assets and MES or CSI, respectively. Additionally, for each quintile in MES and CSI, two-sided t-tests on the equality of means of the largest and smallest banks are performed. ***,**, and * denote statistical significance at the 1%, 5%, and 10% level, respectively. The variables and their data sources are defined in Appendix A.2.

Panel A:		MES quintiles				
Total assets quintiles	Smallest	2	3	4	Largest	Average
Smallest	0.0349	0.0229	0.0027	-0.0190	-0.1265	-0.0032
2	0.0131	0.0232	0.0027	-0.0168	-0.1018	-0.0103
3	0.0398	0.0107	0.0005	-0.0159	-0.1185	-0.0148
4	0.0359	0.0265	0.0132	-0.0167	-0.1422	-0.0207
Largest	0.0326	0.0337	0.0250	-0.0141	-0.1320	-0.0382
Largest - smallest	-0.0023	0.0108	0.0223**	0.0049	-0.0055	-0.0350***

Panel B:		CSI quintiles				
Total assets quintiles	Smallest	2	3	4	Largest	Average
Smallest	-0.0238	-0.0016	0.0050	-0.0112	-0.0472	-0.0126
2	-0.0278	-0.0036	-0.0058	-0.0220	-0.0215	-0.0160
3	-0.0084	-0.0182	-0.0011	-0.0320	-0.0378	-0.0193
4	-0.0270	0.0007	-0.0106	-0.0292	-0.0874	-0.0310
Largest	-0.0374	-0.0179	-0.0143	-0.0454	-0.0889	-0.0432
Largest - smallest	-0.0136	-0.0163	-0.0193	-0.0342**	-0.0417**	-0.0307***

Table V: Panel regressions of bank performance 2004-2012.

The table presents results of panel regressions of quarterly buy-and-hold returns on the General crisis sentiment index, the FEARS index, and the CSI, respectively, and on various control variables. The sample consists of 413 international banks over the sample period from January 2004 to December 2012. Models (1) - (3) are estimated using the full sample while (4) - (6) are restricted to the top quartile of banks' total assets. The remaining estimates in (7) - (9) are concerned with the top quartiles of banks' size during the crisis period of 2006-2010. All regressions are estimated with fixed effects and clustered standard errors. All explanatory variables are lagged by one quarter and p-values are reported in parentheses. Variable definitions and data sources are provided in Appendix A.2. ***,**,* denote statistical significance at the 1%, 5%, and 10% level, respectively.

Sample	Full			Large			Large × Crisis		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
CSI	0.0104			-0.0391			-0.0334		
	(0.744)			(0.495)			(0.691)		
General CSI		-0.0007*			-0.0022***			-0.0020**	
		(0.086)			(0.007)			(0.014)	
FEARS			-0.0671***			-0.2032***			(omitted)
			(0.007)			(0.000)			
Size	-0.0499**	-0.0553***	-0.0553***	-0.0370	-0.0372	-0.0372	-0.0052	-0.0735**	-0.0735**
	(0.011)	(0.000)	(0.000)	(0.221)	(0.115)	(0.115)	(0.919)	(0.047)	(0.047)
Return on assets	0.0024	0.0030	0.0030	0.0123	0.0109	0.0109	0.0382*	0.0031	0.0031
	(0.771)	(0.637)	(0.637)	(0.385)	(0.303)	(0.303)	(0.067)	(0.836)	(0.836)
Market-to-book ratio	0.0315***	0.0133*	0.0133*	0.0479***	0.0051	0.0051	0.0553***	0.0033	0.0033
	(0.000)	(0.072)	(0.072)	(0.001)	(0.186)	(0.186)	(0.000)	(0.287)	(0.287)
Leverage	-0.0013***	-0.0013***	-0.0013***	-0.0011***	-0.0012***	-0.0012***	-0.0011***	-0.0012***	-0.0012***
	(0.000)	(0.000)	(0.000)	(0.001)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Non-interest income	0.1858***	0.1267***	0.1267***	0.2105***	0.1707***	0.1707***	0.2361***	0.2009***	0.2009***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.001)	(0.001)	(0.000)	(0.000)	(0.000)
Loans	-0.0835*	-0.0050	-0.0050	-0.1930	-0.0972	-0.0972	-0.3727**	-0.3078**	-0.3078**
	(0.065)	(0.904)	(0.904)	(0.103)	(0.168)	(0.168)	(0.018)	(0.015)	(0.015)
Distance-to-default	0.0063	0.0037	0.0037	0.0154***	0.0075	0.0075	-0.0138	-0.0019	-0.0019
	(0.185)	(0.202)	(0.202)	(0.000)	(0.164)	(0.164)	(0.373)	(0.854)	(0.854)
Tier 1 capital	0.0001	0.0004	0.0004	0.0048	0.0052*	0.0052*	0.0010	0.0067	0.0067
	(0.750)	(0.217)	(0.217)	(0.153)	(0.094)	(0.094)	(0.878)	(0.119)	(0.119)
MES	-0.0205	0.1387	0.1387	-0.6000	0.1697	0.1697	-1.7298**	-0.2520	-0.2520
	(0.957)	(0.663)	(0.663)	(0.384)	(0.733)	(0.733)	(0.031)	(0.654)	(0.654)
Bank-fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Time-fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	4,616	8,533	8,533	1,517	2,702	2,702	746	1,293	1,293
Adjusted R^2	0.390	0.352	0.352	0.553	0.513	0.513	0.532	0.496	0.496

Table VI: Panel regressions in the first and fourth quartile of default risk, leverage, market-to-book ratio, and MES.

The table presents results of panel regressions of quarterly buy-and-hold returns on the General crisis sentiment index and the idiosyncratic CSI, respectively, and on various control variables. Our sample is split into the first and fourth quartile of a bank's default risk (Panel A), leverage (Panel B), market-to-book ratio (Panel C), and Marginal Expected Shortfall (Panel D). All regressions are estimated with fixed effects and clustered standard errors at the firm level. All explanatory variables are lagged by one quarter and p-values are reported in parentheses. Other controls include the variables from the baseline regressions. Crisis is a dummy variable that is one if the observation is in 2006-2010 and zero otherwise. Variable definitions and data sources are provided in Appendix A.2. ***,**,* denote statistical significance at the 1%, 5%, and 10% level, respectively.

Panel A: Quartile of Distance-to-default	1st	4th	1st	4th	1st	4th
General CSI	-0.0026***	0.0005				
	(0.003)	(0.603)				
CSI			0.0819	0.1138*		
			(0.155)	(0.056)		
CSI × Crisis					0.1832	-0.0627
					(0.184)	(0.727)
Panel B: Quartile of Leverage	1st	4th	1st	4th	1st	4th
General CSI	-0.0008	-0.0024***				
	(0.290)	(0.000)				
CSI			-0.0144	-0.0293		
			(0.824)	(0.631)		
CSI × Crisis					0.0151	-0.2662**
					(0.911)	(0.019)
Panel C: Quartile of Market-to-book ratio	1st	4th	1st	4th	1st	4th
General CSI	-0.0011	-0.0002				
	(0.142)	(0.808)				
CSI			-0.0719	0.0280		
			(0.266)	(0.640)		
CSI × Crisis					-0.2184*	0.2595
					(0.071)	(0.111)
Panel D: Quartile of MES	1st	4th	1st	4th	1st	4th
General CSI	-0.0023***	-0.0012				
	(0.000)	(0.181)				
CSI			0.0837	0.0898		
			(0.128)	(0.142)		
CSI x Crisis					0.2033**	0.0842
					(0.021)	(0.325)
Other controls	Yes	Yes	Yes	Yes	Yes	Yes
Bank-fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Time-fixed effects	Yes	Yes	Yes	Yes	Yes	Yes

Table VII: Panel regressions of stock performance for banks and non-financial firms.

The table presents results of panel regressions of quarterly buy-and-hold returns on the General crisis sentiment index (CSI) and the idiosyncratic CSI, respectively, and on various control variables. The sample consists of 413 international banks and 756 non-financial companies for the period from January 2004 to December 2012. All regressions are estimated with fixed effects and clustered standard errors. The estimates in the columns (1) - (4) are concerned with baseline regressions for the full sample of banks and the crisis period from 2006 to 2010. Columns (5) - (8) present the estimates for an international sample of non-financial firms. All explanatory variables are lagged by one quarter and p-values are reported in parentheses. Variable definitions and data sources are provided in Appendix A.2. ***,**,* denote statistical significance at the 1%, 5%, and 10% level, respectively.

	Banks				Non-financial firms			
Sample	Full	Full	Crisis	Crisis	Full	Full	Crisis	Crisis
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
CSI	0.0293		0.0540		-0.0006		-0.0273	
	(0.295)		(0.248)		(0.967)		(0.248)	
General CSI		-0.0022***		-0.0014***		-0.0063***		-0.0073***
		(0.000)		(0.001)		(0.000)		(0.000)
Size	-0.0552***	-0.0610***	-0.1595***	-0.1414***	-0.0475***	0.0256	-0.0683***	-0.0700***
	(0.001)	(0.000)	(0.000)	(0.000)	(0.000)	(0.598)	(0.000)	(0.000)
Return on assets	0.0120***	0.0121***	0.0069*	0.0056*	0.0015***	0.0014***	0.0014***	0.0012***
	(0.009)	(0.000)	(0.089)	(0.068)	(0.000)	(0.000)	(0.005)	(0.009)
Market-to-book ratio	0.0002	0.0009	0.0009	0.0018	0.0055	-0.0266	0.0172***	0.0176***
	(0.702)	(0.389)	(0.372)	(0.262)	(0.123)	(0.224)	(0.001)	(0.002)
Leverage	0.0000	-0.0001	-0.0001	-0.0002	-0.0025**	-0.0028**	-0.0048***	-0.0035***
	(0.786)	(0.511)	(0.388)	(0.218)	(0.015)	(0.019)	(0.009)	(0.007)
Bank-fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Time-fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	6,607	12,352	3,178	5,814	21,789	24,834	10,148	11,373
Adjusted R^2	0.3321	0.3143	0.3118	0.2975	0.3578	0.3366	0.3691	0.3703

Table VIII: Robustness checks.

The table presents results of further panel regressions performed as robustness checks of our main results. We regress the banks' quarterly buy-and-hold returns on proxies for idiosyncratic crisis sentiment as well as market-wide crisis sentiment, respectively, and on various control variables. The sample includes 413 international banks over the time period from Q1 2004 to Q4 2012. Columns (1)-(4) present the results for our panel regressions using the full sample while columns (5)-(8) are concerned with regressions in the fourth quartile of a bank's total assets. Aside from bank characteristics, these models employ variables on internet usage among a country, general indicators for the respective economy in a country, as well as variables describing the regulatory differences between the countries in our sample. All regressions are estimated with bank- and time-fixed effects and clustered standard errors at the firm level. Variable definitions and data sources are provided in Appendix A.2. Numbers in parentheses are p-values and ***,**, and * denote statistical significance at the 1%, 5%, and 10% level, respectively.

Sample	Full				Large			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
CSI	0.0021				-0.0345			
	(0.947)				(0.535)			
General CSI		-0.0016***	-0.0020***	-0.0011**		-0.0030***	-0.0042***	-0.0017*
		(0.000)	(0.002)	(0.025)		(0.000)	(0.001)	(0.058)
FEARS		0.2358***	0.2362***			0.2426***	0.2439***	
		(0.000)	(0.000)			(0.000)	(0.000)	
Size	-0.0475**	-0.0506***	-0.0494***	-0.0492***	-0.0393	-0.0301	-0.0299	-0.0307
	(0.025)	(0.000)	(0.001)	(0.001)	(0.182)	(0.188)	(0.190)	(0.166)
Internet use	-0.0014**	-0.0014**	-0.0015**	-0.0027***	-0.0010	-0.0028***	-0.0030***	-0.0050***
	(0.025)	(0.015)	(0.013)	(0.000)	(0.298)	(0.004)	(0.003)	(0.001)
GDP	0.0028	0.0026*	0.0026*	0.0019	-0.0002	0.0013	0.0016	-0.0014
	(0.173)	(0.060)	(0.056)	(0.239)	(0.960)	(0.613)	(0.559)	(0.540)
Inflation	0.0005	-0.0001	-0.0001	0.0010	0.0026	0.0027	0.0027	-0.0029
	(0.536)	(0.894)	(0.915)	(0.169)	(0.559)	(0.379)	(0.379)	(0.297)
Stock market turnover	-0.0001	0.0000	0.0000	0.0001	0.0000	0.0000	0.0000	0.0001
	(0.232)	(0.499)	(0.349)	(0.119)	(0.846)	(0.989)	(0.803)	(0.575)
General CSI x Internet use			0.0000				0.0000	
			(0.399)				(0.274)	
Restrictions on banking activities				0.0019				0.0004
				(0.583)				(0.941)
Capital regulatory index				0.0019				-0.0006
				(0.441)				(0.867)
Supervisory power index				-0.0038***				-0.0024
				(0.009)				(0.320)
Independence of supervisors				0.0028				0.0047
				(0.591)				(0.466)
Deposit insurance				0.0025				0.0122
				(0.853)				(0.555)
Bank controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Bank-fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Time-fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	4,513	8,307	8,307	5,300	1,511	2,684	2,684	1,869
Adjusted R^2	0.392	0.354	0.354	0.454	0.554	0.517	0.517	0.585